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MARKETS AND MARKUPS: A NEW EMPIRICAL FRAMEWORK AND EVIDENCE ON EXPORTERS FROM CHINA

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Markets and Markups:

A New Empirical Framework and Evidence on Exporters from China

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Abstract

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JEL classification: F31, F41

Keywords: exchange rates, pricing-to-market, product classification, differentiated goods, markup elasticity, trade elasticity, China.

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1 Introduction

A fundamental feature of international goods markets is that firms exporting to more than one destination account for the lion’s share of cross-border trade. Serving multiple markets, these firms face demand conditions and market structures that differ across locations and are inherently time-varying. Indeed, global and local shocks to fundamentals, as well as country-specific economic policies, bear upon how much competition exporters endure from local and other international producers. Effectively, from the perspective of an exporter, a changing local economic environment systematically creates opportunities to raise profits, or induces the need to contain losses, through destination-specific adjustment of export prices, i.e., by engaging in pricing-to-market (Krugman (1986) and Dornbusch (1987)).

Trade globalization has heightened the importance of understanding the many factors that drive a global firm’s pricing strategy. Indeed, pricing-to-market is already a standard feature in open macro models, increasingly featuring firm dynamics and competition (see, e.g., Bergin and Feenstra (2001) and Atkeson and Burstein (2008)), vertical interactions of exporters with local producers and distributors (see, e.g., Corsetti and Dedola (2005)), and nominal rigidities in either local or a (third-country) vehicle currency (Corsetti, Dedola and Leduc (2008), Gopinath (2015) and Casas, Diez, Gopinath and Gourinchas (2017)).¹ By the same token, the increasing availability of high-dimensional administrative customs databases has already been providing a wealth of new insights about the pricing behaviour of firms (see, e.g., Berman, Martin and Mayer (2012), Chatterjee, Dix-Carneiro and Vichyanond (2013), Amiti, Itskhoki and Konings (2014), Fitzgerald and Haller (2014), De Loecker, Goldberg, Khandelwal and Pavcnik (2016), Fitzgerald and Haller (2018)). However, there is a sense in which research has yet to fully exploit the data in all its dimensions—and in ways that can inform our understanding and modelling of multilateral competition by exporters in local and global markets.

In this paper, we build an empirical framework suitable for analyzing the local or *destination-specific* markup and quantity adjustments of multi-destination exporters in firm and product-level administrative datasets.² Applying our framework to exporters from China, we show that, on

¹Leading questions to address range from imported inflation and the consequences of large depreciations to efficiency losses from currency misalignments and the design of stabilization policy in an open economy (Engel (2011) and Corsetti, Dedola and Leduc (2018)).

²Our framework has been specifically developed for application to large, four-dimensional (firm-product-destination-time) unbalanced *customs databases* which cover the universe of firm and product level export records for a country. Recent papers (Berman, Martin and Mayer (2012), Amiti, Itskhoki and Konings (2014), and De Loecker, Goldberg, Khandelwal and Pavcnik (2016)) have proposed different methodologies aimed at identifying marginal costs and markups, using detailed information on production and costs, including prices and costs of domestic and imported inputs. An advantage of these methodologies over our analysis is that they provide estimates of the overall level of markups. An advantage specific to our methodology, however, is a much lower data requirement and a larger range of applicability to standard customs datasets. We obviously see strong complementarities and high potential gains from combining methodologies and cross checking results.

average, firms engage in significant pricing to market: the destination-specific markup elasticity to exchange rate movements is far from negligible, especially for highly differentiated goods (20%) as opposed to less differentiated goods (6%). We also show that differences in pricing to market across types of goods nicely map into significantly different elasticities for the quantity supplied across destinations. These are much lower for highly differentiated goods (.83) than for less differentiated goods (2.47): intuitively, a muted response of local prices in local currency implies a smaller variation in sales.

On methodological grounds, our contribution is twofold. First, we construct an estimator of the markup elasticity to the exchange rate that exploits multiple destination-specific prices of individual products in order to net out changes in unobserved marginal costs—that we dub the Trade Pattern Sequential Fixed Effects (TPSFE) estimator. The general approach builds on the seminal work by [Knetter \(1989\)](#). However, unlike Knetter’s original method, our estimator is free of the bias introduced when firms endogenously discontinue or open destination markets in response to exchange rate fluctuations—implying that the panel of observations is endogenously unbalanced ([Han 2017, 2018](#)). We derive a identification condition stating the assumptions required for our proposed TPSFE estimator to be unbiased—a condition that is weaker than typically imposed in the pricing-to-market literature.

Based on the TPSFE, we show how to estimate the market-specific responsiveness of *quantities* to currency fluctuations. We propose a two-stage procedure. In the first stage, we estimate the predicted changes in relative markups that stem from movements in relative exchange rates using our TPSFE estimator; in the second stage, we regress changes in relative quantities across destinations on the predicted relative markup changes and other aggregate control variables conditional on the firm and product-level trade patterns.³ As our estimator differences out common supply factors, the second stage measures the degree to which the quantity supplied responds to shifts in relative profitability across destinations due to changes in relative markups (which, in turn, arise from differences in local factors which shift the relative demand curve). We refer to this measure as the within-firm cross market supply elasticity (CMSE).⁴

Second, the intensity of competition among firms varies not only with local market structure,

³The conventional approach to investigate quantity responses to exchange rates, as taken for example by [Berman, Martin and Mayer \(2012\)](#), directly regresses quantities on exchange rates. Apart from the difficulty in controlling the marginal cost, the conventional method would in general underestimate the heterogeneity in quantity responses across products and firms. This arises from the duality property of markup responses – a high markup elasticity often originates from a market structure with low substitutability that is associated with a low quantity response.

⁴This is developed for highly-disaggregated data along the lines of work by [Feenstra \(1994\)](#) and [Broda and Weinstein \(2006\)](#), estimating import demand and export supply elasticities. The elasticity is similar to the cross-destination trade value response to tariffs in [Bown and Crowley \(2007\)](#), but introduces a new identification strategy. Our CMSE elasticity potentially provides an alternative measure of market power in a multi-country context that complements empirical studies characterizing the relationship between market share and optimal exchange rate pass through, e.g., [Feenstra, Gagnon and Knetter \(1996\)](#) and [Auer and Schoenle \(2016\)](#).

but also systematically across different types of globally-traded products—producers of highly differentiated manufactured goods hold more pricing power than producers of undifferentiated commodities. Our methodological contribution here is a novel product classification of traded goods into categories of market power, or, equivalently, the degree of product differentiation. The core idea is a simple one: traded goods whose quantity is recorded in customs data by weight or volume are less differentiated than goods whose quantity is reported in countable units. Chinese customs data provide a unique opportunity to extend this simple idea into an exogenous classification system because the choice to record a product’s quantity in units versus mass is predetermined by Chinese grammar and linguistics. We exploit linguistic information on “measure words” recorded in the Chinese Customs Database to construct a general product classification for the Harmonized System.

Our classification improves the popular classification by [Rauch \(1999\)](#) in two ways. First, and most importantly, we break down Rauch’s large class of differentiated manufactured goods into two similarly-sized groups, distinguishing high and low differentiation products. Applying [Rauch \(1999\)](#)’s categories, we find about 80 percent of Chinese exports (observation weighted) are classified as differentiated. According to our Corsetti-Crowley-Han-Song (CCHS) linguistics-based classification, about half of these, amounting to 39 percent of all Chinese exports, are actually highly differentiated, while 41 percent exhibit low differentiation. Second, many products that are left unclassified by Rauch can be classified as high or low differentiation goods according to CCHS.

On empirical grounds, we apply our methodology to multi-destination exporters from China using annual data on firm-product-destination exports over 2000-2014.⁵ This period includes both the last years of the dollar-peg regime (2000-2005) and the early years of the more relaxed managed float (2006-2014). The invoicing currency of Chinese exports is not recorded in our dataset, but the US dollar is widely-held to have been the principal invoicing currency for Chinese exports throughout this period.⁶ Because exports to the US were subject to two different exchange rate regimes during our sample period, we exclude exports to the US in order to obtain a comparable sample of countries over the full sample period.⁷ After merging available macroeconomic data and eliminating single-destination and single-year exporters, the sample consists of over 200,000 multi-destination exporters, around 8,100 HS08 products, and 154 foreign markets over 15 years. We implement our TPSFE estimator conditional on price changes; our results are therefore fully comparable with recent estimates of exchange rate pass through (ERPT) derived using the approach

⁵The database consists of monthly records by firm-product-destination for 2000-2006 and annual records by firm-product-destination for 2007-2014. We aggregate the monthly data for 2000-2006 to the annual level in our analysis.

⁶See appendix [C.3](#) for evidence on dollar invoicing.

⁷We also omit exports to Hong Kong from our analysis because of the changing importance of its role as an entrepôt over time (see [Feenstra and Hanson \(2004\)](#)). Further, we treat the eurozone as a single economic entity and aggregate the trade flows (quantities and prices) to eurozone destinations at the firm-product-year level.

of Gopinath, Itskhoki and Rigobon (2010) and estimates of markup elasticities by Fitzgerald and Haller (2014).

Our main empirical findings are as follows. First, on average, firms engage in significant pricing-to-market. Over 2006-2014 (after China gave up the dollar peg), our average estimate of the destination-specific markup elasticity is as high as 20% for high differentiation goods, and peaks at 32% for consumption goods characterized by high differentiation. On average, for high differentiation goods, around two-thirds of the price adjustment to the exchange rate is due to a destination-specific markup adjustment. Conversely, markup elasticities are small and close to zero for products that we classify as low differentiation goods—a result that validates our linguistics-based product classification.

Second, we show that destination-specific markup adjustments motivated by exchange rate movements actually map into differentiated quantity responses across markets. In our findings, the difference in the cross-market supply elasticity between consumption goods and intermediates is substantial, 0.54 vs 2.92. When further disaggregated under the CCHS product classification, the gap between estimates opens to a chasm—the CMSE of high differentiation consumption goods, 0.23, suggests an extreme amount of market segmentation. The CMSE for low differentiation intermediates, 3.27, suggests something much closer to an integrated world market.

Lastly, we provide insights into the international pricing strategies of different types of firms operating in China. We distinguish among State Owned Enterprises (SOEs), Foreign Investment Enterprises (FIEs) and private enterprises. Overall, we find a considerably higher degree of markup adjustment as well as a considerably lower degree of exchange rate pass through among SOEs and FIEs, relative to private firms. While our results may in part reflect differences in the average size of firms over the sample period and, possibly, profit-shifting practices, they point to a significantly higher degree of market power among SOEs and FIEs and a substantial divide relative to Chinese private firms.⁸

While the focus of this paper is mainly empirical, we should stress that our methodology is motivated and driven by open economy macro theory. While global and local shocks naturally lead firms to reconsider their pricing strategies, their choice sets are not unconstrained, but crucially reflect the extent to which firms have power in local markets and can keep the foreign markets for their products segmented to minimize arbitrage. For example, an exporting firm must consider not only the direct effect of changes in the value of its own currency on own competitiveness, but also the response of foreign rivals to swings in the bilateral exchange rates between destination markets and third countries—as this has key implications for the firm’s residual demand and, hence, local pricing power. In this sense, a multilateral analysis of markup and quantity elasticities can provide

⁸Differences in the average size of different types of firms, with private firms having much lower export values on average might simply reflect the high rate of entry of new cohorts of young, private firms.

fundamental insight into the effective degree of competition within and across markets, especially if articulated by product and firm characteristics.

In this respect, the destination-specific markup elasticity (DSME) and the cross-market supply elasticity (CMSE) together can offer a novel and important diagnostic tool to guide and discipline the development of open-economy models. In ongoing work, we are developing a multi-country model with features drawn from leading contributions in the literature (Corsetti, Crowley and Han 2018). Our results suggest that specific theoretical elements - especially multilateral competition among producers of substitutes and vertical interactions between producers and distributors – are necessary to capture the important aspects of observed behaviour revealed in our elasticities.

The rest of the paper is organized as follows. Section 2 presents our empirical framework. Section 3 summarizes the database. Section 4 presents our empirical results. In section 5 we apply our estimator to studying pricing by different groups of firms operating in China. Section 6 concludes.

2 Empirical Framework

In this section, we introduce an empirical framework designed to study adjustments to markups and quantities of products sold by firms across multiple foreign markets. We first present our Trade Pattern Sequential Fixed Effect Estimator (TPSFE), suitable for estimating markup elasticities to changes in destination-specific conditions while controlling for unobserved product-level marginal cost within a firm in an environment with endogenous market selection. Second, we show how to use the logic of the TPSFE to construct an estimator of adjustmentst to quantities sold in response to changes in *relative* market conditions; this estimator sheds new light on how destination-specific markup adjustments translate into changes in quantities sold across markets. Lastly, we describe a new classification for Harmonized System products which distinguishes between high and low differentiation goods and thus serves as a useful proxy for firms’ market power.

2.1 Estimating a markup elasticity with a large customs database

A typical customs database records information on export values and quantities that varies along at least four dimensions: product, firm, foreign destination, and time. Let p_{ifdt} denote the logarithm of the price (approximated by the unit value) of good i , produced by firm f and sold in destination d in year t . The optimal price p_{ifdt} can always be decomposed into a markup component, μ_{ifdt} , and a marginal cost component mc_{ifdt} :⁹

⁹In appendix A.1, we show how the optimal price of a firm under any (static) pricing problem can always be decomposed into a markup component solely explained by the demand elasticity with respect to price and a marginal cost component.

$$p_{ifdt} = \mu_{ifdt} + mc_{ifdt} \quad (1)$$

where all the terms above are denominated in the exporter’s currency. The key question motivating our analysis is how to assess the response of the firm’s product markup in a destination market to a change in the local market condition measured by e_{dt} ¹⁰, that is:

$$\frac{\partial \mu_{ifdt}}{\partial e_{dt}} = \frac{\partial p_{ifdt}}{\partial e_{dt}} - \frac{\partial mc_{ifdt}}{\partial e_{dt}} \quad (2)$$

A major obstacle in obtaining markup elasticities, is that the marginal cost is unobserved and is highly likely to be correlated with e_{dt} directly through imported inputs (see e.g., [Amiti, Itskhoki and Konings \(2014\)](#)) or indirectly, due to general equilibrium movements in the prices of factors of production (e.g., wages).¹¹ This obviously creates a daunting challenge for empirical analyses.¹²

One way to approach our question consists of constructing an estimate of marginal costs—a step that would require detailed firm-level information in conjunction with the customs dataset. Using balance sheet data, leading contributions have estimated productivity and marginal cost at the firm level [e.g., [Berman, Martin and Mayer \(2012\)](#) and [Amiti, Itskhoki and Konings \(2014\)](#)]. In relation to our question of interest, however, following this approach would confront us with a key issue. Even if we could obtain data on firms, information on production inputs would generally be available at the firm level—not at the firm-product level.¹³ Without some assumptions on how inputs are allocated across products and destinations, it would not be possible to estimate marginal cost at the firm-product-destination level. By way of example, the seminal contribution by [De Loecker, Goldberg, Khandelwal and Pavcnik \(2016\)](#) estimates firm-product level marginal costs and markups under the assumption that the production functions of single-product firms are representative of those of multi-product firms.

The alternative approach that we follow has a much lower data requirement, i.e., it relies exclusively on customs data, and consists of exploiting variation across destination markets, in the

¹⁰Throughout our analysis, we will focus on (differences in) movements of bilateral exchange rates across destination markets as the main source of variation. Nonetheless, our framework can be applied to study markup and quantity adjustments more generally, conditional on identified shocks to a variety of economic and policy disturbances, including changes in trade costs and tariffs.

¹¹For example, a positive home productivity shock that lowers the marginal cost of home producers may also appreciate the home currency against its trade partners.

¹²See [Goldberg and Knetter \(1997\)](#) and [Corsetti, Dedola and Leduc \(2008\)](#) for a discussion. Analysis of exchange rate pass through and deviations from the Law of One Price has been the focus of an extensive literature including [Engel and Rogers \(1996\)](#), [Crucini and Shintani \(2008\)](#), and [Cavallo, Neiman and Rigobon \(2014\)](#).

¹³We should stress that, in most countries, the mapping between customs databases and industrial-survey data is often incomplete, raising issues of sample selection. In addition, balance sheet data means information is only available at annual frequencies, making it impossible to carry out the analysis at a higher frequency (monthly or quarterly).

spirit of [Knetter \(1989\)](#).¹⁴ Exploiting the fact that most firms sell each of their products to multiple destinations, one can obtain an estimator that controls for changes in the unobservable product-level marginal cost within a firm over time by taking differences of prices across destination markets. Intuitively, we write the components of the price for product i sold by a firm in a destination in terms of the residual from the average of each component across destinations, as follows:

$$\frac{\partial \mu_{ifdt}}{\partial e_{dt}} - \frac{1}{n_{ift}^D} \sum_{d \in D_{ift}} \frac{\partial \mu_{ifd't}}{\partial e_{d't}} = \left[\frac{\partial p_{ifdt}}{\partial e_{dt}} - \frac{1}{n_{ift}^D} \sum_{d \in D_{ift}} \frac{\partial p_{ifd't}}{\partial e_{d't}} \right] - \left[\frac{\partial mc_{ifdt}}{\partial e_{dt}} - \frac{1}{n_{ift}^D} \sum_{d \in D_{ift}} \frac{\partial mc_{ifd't}}{\partial e_{d't}} \right] \quad (3)$$

where n_{ift}^D and D_{ift} denote, respectively, the number and set of destination markets in which the firm sells product i at time t , with $d_{ift} \in D_{ift}$. Two challenges arise in applying this differences-across-destinations method to identifying destination-specific markups. First, destination-specific costs, if any exist, could prevent the second term in brackets in equation (3) from being equal to zero. Second, the set of destination markets D_{ift} at the firm-product level is not constant but can grow or shrink over time in response to changes in local conditions.

Our contribution to this identification strategy is twofold. First, we derive the assumptions required for identification strategies which exploit variation across destinations to produce unbiased estimates. These assumptions, synthesized in a single identification condition, can be given a structural interpretation, that we detail in the appendix [B.5](#).

Second, we address the market selection problem in applying this identification strategy to highly disaggregated firm-product-destination level datasets. Building on [Han \(2017\)](#), we propose a Trade Pattern Sequential Fixed Effect (TPSFE) estimator that controls for possible endogenous selection of markets by conditioning estimates on the trade patterns of firms and products.

2.1.1 Identification condition

We start by writing an expression for marginal costs that allows for the possibility that variation depends not only on the firm and the product, but also on the destination:

$$mc_{ifdt} = \overline{mc}_{ift} + \psi_{ifdt} \quad (4)$$

where

$$\overline{mc}_{ift} \equiv \frac{1}{n_{ift}^D} \sum_{d \in D_{ift}} mc_{ifdt} \quad \text{and} \quad \psi_{ifdt} \equiv mc_{ifdt} - \overline{mc}_{ift}$$

¹⁴[Knetter \(1989\)](#) studies responses of product level price indices to exchange rates. To control for product level marginal cost, this author adds destination fixed effects—a methodology that is suitable if the panel of observations is *balanced*, as is the case for *industry-level* price indices.

The first term, \overline{mc}_{ift} , is the mean marginal cost, averaged across destinations for firm f 's product i at time t (denominated in the exporter's currency). The second term, ψ_{ifdt} captures any destination-specific components of marginal cost. More generally, as we observe unit values, this second term allows us to handle possible changes in the composition of varieties shipped under a particular product code to specific destinations. This possibility implies that ψ_{ifdt} can be nonzero, even if the marginal cost of each variety has no destination-specific component.

The general condition for an estimator of the markup elasticity that exploits cross-destination variation to be unbiased is:¹⁵

$$\frac{1}{n^{DT}} \sum_d \sum_t (\overline{\psi}_{dt} - \overline{\psi}_d)(e_{dt} - \overline{e}_d) = 0 \quad (5)$$

where \overline{x}_j is the mean of variable x taken over all dimensions other than j . n^{DT} is the total number of destination-time periods. (For example, in a balanced panel, n^{DT} is the number of destinations n^D times the number of time periods n^T .) The term $(\overline{\psi}_{dt} - \overline{\psi}_d)$ measures the deviations of the average destination-specific marginal cost component across firms and products within a destination over time. The term $(\overline{e}_{dt} - \overline{e}_d)$ measures deviations of the bilateral exchange rate from its long-run mean over time.

The condition (5) is trivially satisfied if $\psi_{ifdt} = 0$, that is, if the goods sold to different destinations under the same product code are identical at the firm-product level. More crucially, however, the condition clarifies that the possibility of destination-specific components in marginal costs ($\psi_{ifdt} \neq 0$) does not automatically lead to a violation of identification. An important instance in which condition (5) is satisfied occurs when the cross-destination distribution of the destination-specific component does not change over time, e.g., high quality varieties of a product are consistently sold to rich destinations.

It is worth stressing that the condition 5 requires no assumption on firm and product idiosyncratic shocks, and is weaker than orthogonality of the destination-specific marginal cost component ψ_{ifdt} and the bilateral exchange rate e_{dt} , a condition which has been emphasized in the literature on exchange rate pass through (see, e.g., Corsetti, Dedola and Leduc (2008)). Note that only the mean of the destination-specific marginal cost component across all firms and products, $\overline{\psi}_{dt}$, enters the condition (5).

To conclude, it can be shown that the above condition is implicit in studies aimed at estimating productivity (as these do not try to distinguish the marginal cost at the destination level)—see, e.g., Olley and Pakes (1996), Levinsohn and Petrin (2003), Wooldridge (2009) and De Loecker, Goldberg, Khandelwal and Pavcnik (2016).¹⁶

¹⁵See appendix B for the derivation of (5) and a detailed extensive discussion.

¹⁶Olley and Pakes (1996), Levinsohn and Petrin (2003) and Wooldridge (2009) estimate firm-level productivity and

2.1.2 Trade Pattern Sequential Fixed Effects (TPSFE)

In this subsection, we introduce and discuss our estimator. As mentioned previously, our estimation strategy consists of differencing out the unobserved marginal costs by expressing all the observations on product i sold by firm f to multiple destinations at time t , in terms of deviations from their average. At each point in time, this average will be conditional on the set of destination markets chosen by the firm. This presents a problem if the choice of markets is endogenous to the exchange rate. Hence, if we use price residuals as our measure of the relative markup in each destination and compare these price residuals over time, this comparison will generally confound genuine changes in the relative markup for each destination with changes in the “measured” markup that arise due to recalculating the mean conditional on different sets of destinations.¹⁷

To make sure that our empirical results are not contaminated by this problem, we propose an approach based on a comparison of observations for identical trade patterns—these are defined as sets of destinations that may repeat identically in a subset of years in our sample for each product sold by a firm.¹⁸ We then specify a regression model with trade pattern fixed effects – in fact, a firm that exports to multiple sets of destinations over our sample period is assigned multiple trade pattern fixed effects – one for each of the firm’s observed trade patterns. Each trade pattern fixed effect is turned on in the years in which the firm sells to that particular set of countries. In other words, we regress product prices in deviations from means on exchange rates, controls and the trade-pattern fixed-effect. This approach ensures that, when we compare observations over time, these are always calculated as deviations from a mean from an identical set of destination markets.

thus can infer the average marginal cost over all products and destinations at the firm level. De Loecker, Goldberg, Khandelwal and Pavcnik (2016) estimates the average marginal cost over destinations at the firm-product level. As an exercise, in appendix B.5, we explore an extension of De Loecker, Goldberg, Khandelwal and Pavcnik (2016) in which we add a destination dimension to production costs. We discuss the assumptions that would be required in a structural framework for (5) to be satisfied. Specifically, we allow the functional form of the production function to be firm-product specific with a log-additive productivity term that is firm-product-destination specific. Note that De Loecker, Goldberg, Khandelwal and Pavcnik (2016) would not be identifiable under these assumptions as their identification strategy requires some degree of separability in the functional form in which they have assumed the production function to be product-specific and the Hicks-neutral productivity to be firm-specific. In this extended framework, we show that our identification strategy recovers an unbiased estimate of the markup elasticity even when the marginal cost at the firm-product level varies across destinations, but only if the production function is constant return to scale. It is only when changes in relative demand across destinations lead to relative changes in quantities (which are associated with changes in destination-specific marginal cost) that condition (5) will be violated. This is only the case if the production function is destination-specific. Under the standard assumptions of De Loecker, Goldberg, Khandelwal and Pavcnik (2016) where the production function is not destination-specific, our estimator yields unbiased estimates with constant return to scale (CRS), increasing return to scale (IRS) and decreasing return to scale (DRS) production functions.

¹⁷ If the variation in the set of destinations observed in each period is random, that is, if it is not driven by the exchange rate, then it can be shown that an estimator that works in a balanced panel also works in an unbalanced one (see appendix). However, if the set of destination is systematically related to the exchange rate, the estimates will be biased.

¹⁸See the appendix C.4 for a detailed discussion and an example.

In other words, the comparison is ‘apples-to-apples’ across sets of firm-product prices in different periods. We dub this estimator, which is designed to address the bias associated with endogenous shifts in destinations, “trade pattern sequential fixed effects” (TPSFE).¹⁹

We leave a rigorous derivation and a comparative analysis of the TPSFE estimator to the appendix (see Appendix B) and, for now, describe its implementation via a four-step procedure.

1. Demean each variable in the dataset at the firm-product-time level, so to express each variable as a destination-specific deviation from the mean. This step strips out a firm’s time-varying marginal production cost, as well as any global factor that is common across all the destinations a firm serves.
 - (a) For each firm-product-time triplet, calculate the mean of each dependent and independent variable over all active destinations of the firm in that period, i.e., calculate:

$$\frac{1}{n_{ift}^D} \sum_{d \in D_{ift}} x_{ifdt} \quad \forall x \in \{p_{ifdt}, e_{dt}, X_{dt}\} \quad (6)$$

where n_{ift}^D is the number of active foreign destinations for each product of a firm in year t and D_{ift} denotes the set of destinations, d , in which the firm f is selling its product i in period t .

- (b) Subtract the mean over active destinations in order to obtain the residual variation in the variable by destination, conditional on the observed trade pattern in that period, indicated by the subscript D_{ift} :

$$\tilde{x}_{ifdt, D_{ift}} = x_{ifdt} - \frac{1}{n_{ift}^D} \sum_{d \in D_{ift}} x_{ifdt} \quad \forall x \in \{p_{ifdt}, e_{dt}, X_{dt}\} \quad (7)$$

2. Define the trade pattern fixed effect for each product sold by a firm in each time period.

For each firm-product-time (f, i, t) triplet:

- (a) Identify the set of destinations observed for this triplet and generate a string variable, denoted D_{ift} , for it. For example, if firm f selling i in year t has positive values of trade

¹⁹The importance of bias in unbalanced panels with selection has long been discussed in labor economics, and is obviously a general econometric problem. After developing our estimator, we were made aware of the work of [Correia \(2017\)](#), who proposes a general multi-dimensional fixed effects estimator (we thank Thierry Mayer for bringing this work to our attention). However, it is important to stress a subtle but important difference between our approach and Correia’s, as a mechanical application of the latter would not work in our context. The correct set of partitioning is essential to avoid introducing changes in the dimensions along which the unobserved marginal cost varies. See appendix B for an extensive discussion. It is also important to stress that there is no unique way to correctly partition multidimensional data because it will depend on the context of the question being examined. For example, see [Fitzgerald, Haller and Yedid-Levi \(2016\)](#) who thoughtfully and appropriately partition high-dimensional Irish customs data in their analysis of firm-level export dynamics.

to Japan, Korea, and Vietnam, assign the value “JP-KR-VN” for the string variable to the three observations associated with firm f ’s sales of i in this year. Note that over time, the same value of the variable D_{ift} will repeat if the firm-product remains active in a set of markets, but it would change to, for example, “JP-KR” if the firm-product ceases to sell to Vietnam.

- (b) Create a unique trade pattern fixed effect that captures each destination along with its associated set of destinations in a time period. For example, sales by firms to Japan in a year when those firms are selling to Japan, Korea, and Vietnam will be assigned the trade pattern fixed effect associated with “JP-JP-KR-VN.” Similarly, in the same period, the firms selling to Korea and Vietnam will be assigned the trade pattern fixed effects for “KR-JP-KR-VN” and “VN-JP-KR-VN,” respectively. Notationally, denote these trade pattern fixed effects as $TP_{d,D_{ift}}$.
- (c) Lastly, control for time-invariant factors that affect the level of the markup within a firm and product to a destination by adding firm and product identifiers to the trade pattern fixed effect. Denote this dummy for the firm, product, and destination-specific trade pattern as $TP_{ifd,D_{ift}}$.

3. Run a regression using destination-demeaned variables and the trade pattern fixed effects.

$$\tilde{p}_{ifdt,D_{ift}} = \kappa_0 + \kappa_1 \tilde{e}_{dt,D_{ift}} + \tilde{X}'_{dt,D_{ift}} \kappa_2 + TP_{ifd,D_{ift}} + \tilde{u}_{ifdt,D_{ift}} \quad (8)$$

where e_{dt} is the bilateral exchange rate (rmb/d) and X_{dt} is a vector of destination-specific macro variables including local CPI and real GDP.

Overall, the reliability of our empirical framework rests on its capacity to address the two fundamental issues we raised at the beginning of this section, the possibility that marginal costs are destination-specific and the endogenous selection of markets.²⁰ To assess the relevance of these issues, in the empirical section below, we compare results from applying our proposed estimator to commonly used alternatives, see 4.3. Relatedly, subsections B.2 and B.3 in the appendix carry out a series of assessments of the bias that may arise from an endogenously unbalanced panel and destination-specific marginal costs under a range of reasonable parameters. Finally, subsection B.5 offers a structural interpretation of the identification condition.

²⁰A recent paper by Han (2018) documents that Chinese firms’ entry into and exit from foreign destinations is a function of bilateral exchange rate movements; this confirms the importance of appropriately controlling for endogenous selection of markets.

2.2 An estimator of firms' cross-market supply elasticity

We now turn to the flip side of the destination-specific markup adjustment, that is, the adjustment of export quantities across destination markets. We are interested in gaining insight into the relationship between destination-specific quantity and markup adjustments within a firm (and product) due to changes in relative demand conditions across destinations.²¹

Towards this goal, we construct the following two-stage estimator. In the first stage, we rely on our TPSFE to obtain predicted prices, $\widehat{p}_{ifdt, D_{ift}}$ using specification (8):

$$\widehat{p}_{ifdt, D_{ift}} = \widehat{\kappa}_0 + \widehat{\kappa}_1 \widetilde{e}_{dt, D_{ift}} + \widetilde{X}'_{dt, D_{ift}} \widehat{\kappa}_2 \quad (9)$$

In the second stage, we use the predicted prices as explanatory variables in the ‘quantity’ equation (10) specified below

$$\widetilde{q}_{ifdt, D_{ift}} = \gamma_0 + \gamma_1 \widehat{p}_{ifdt, D_{ift}} + \widetilde{X}'_{dt, D_{ift}} \gamma_2 + TP_{ifd, D_{ift}} + \widetilde{v}_{ifdt, D_{ift}} \quad (10)$$

Statistically, $\widehat{p}_{ifdt, D_{ift}}$ reflects variation in relative prices driven by changes in the relative market condition measure, $\widetilde{e}_{dt, D_{ift}}$, while controlling for other aggregate variables. The coefficient γ_1 measures the projection of changes in relative quantities on destination-market-condition-driven changes in relative prices.

As long as cost-side factors are perfectly controlled, $\widehat{p}_{ifdt, D_{ift}}$ can be interpreted as the change in *relative markups denominated in the exporter's currency* in response to changes in relative *demand* conditions across destinations.²² As is well known, holding the supply curve fixed, a shift in relative demand induces a movement along the relative supply curve. Heuristically, γ_1 could be seen as the slope of the relative supply curve—that is, it captures the cross-market supply elasticity (CMSE) with respect to destination-specific demand changes.

To appreciate the properties of our estimator, we also run a naïve regression of relative quantity changes on relative prices changes, including trade pattern fixed effects:

$$\widetilde{q}_{ifdt, D_{ift}} = \lambda_0 + \lambda_1 \widehat{p}_{ifdt, D_{ift}} + \widetilde{X}'_{dt, D_{ift}} \lambda_2 + TP_{ifd, D_{ift}} + \widetilde{v}_{ifdt, D_{ift}} \quad (11)$$

As shown in section 4, this naïve regression typically results in a significant but negative correlation: a negative λ_1 indicates that a higher relative price in one destination is on average associated with a lower relative quantity sold by the firm in that destination. In contrast, our two-

²¹ The question can be addressed in different ways. One option is to regress quantities directly on exchange rates using the same specification as our TPSFE for destination-specific markups, (8). However, the option that we prefer consists of regressing quantities on projections of prices on exchange rates. The two procedures yield very similar results.

²² The cost-side factors are controlled if the identification condition (5) is satisfied.

stage procedure generates a positive γ_1 , suggesting that the relative markups and quantities are positively correlated if changes in markups are driven by (relative) demand changes. See appendix A.2 for an analytic discussion.

2.3 A new product classification based on Chinese measure words: Refining Rauch (1999) on high and low differentiation products

For the purpose of our analysis, it is important that we identify products over which firms are potentially able to exploit market power in setting prices. For this identification, most studies adopt the industry classifications set forth by Rauch (1999), according to which a product is differentiated if it does not trade on open exchanges and/or its price is not regularly published in industry sales catalogues. While this system is quite powerful in identifying commodities, a drawback is that the vast majority of manufactured goods end up being classified as differentiated.

We construct a new, finer classification. The core idea is a simple one: traded goods whose quantity is recorded in customs data by weight or volume are less differentiated than goods whose quantity is reported in countable units. Chinese customs data provide a unique opportunity to extend this simple idea into an exogenous classification system because the choice to record a product’s quantity in units versus mass is predetermined by Chinese grammar and linguistics. We exploit linguistic information on “measure words” recorded in the Chinese Customs Database to construct a general product classification for the Harmonized System.

As further detailed below, the Chinese Customs Database reports the universe of China’s exports and imports at the firm and Harmonized System 8-digit (HS08) product level annually from 2000 to 2014. The key variables for our analysis are the export value, the export quantity, and a Chinese-language measure word describing the quantity. The information embedded in the measure word is intrinsically informative about the nature of the good and forms the basis for our classification system. To wit: linguists sort Chinese measure words into two groups—mass classifiers and count classifiers.²³ Count classifiers are used to measure distinct items while mass classifiers are used to measure things that are naturally measured by weight, volume, length, etc.²⁴ Our classification criterion is as follows: any good whose quantity is reported with a count classifier

²³See Cheng and Sybesma (1998) and Cheng and Sybesma (1999) for a discussion of mass classifiers and count classifiers in Chinese. See Fang, Jiquing and Connelly, Michael (2008), *The Cheng and Tsui Chinese Measure Word Dictionary*, Boston: Cheng and Tsui Publishers, Inc. for translations of hundreds of Chinese measure words into English.

²⁴More precisely, Cheng and Sybesma (1998) explain: “while massifiers [mass classifiers] *create* a measure for counting, count-classifiers simply *name the unit* in which the entity denoted by the noun it precedes naturally presents itself. This acknowledges the cognitive fact that some things in the world present themselves in such discrete units, while others don’t. In languages like English, the cognitive mass-count distinction is grammatically encoded at the level of the noun..., in Chinese the distinction seems to be grammatically encoded at the level of the classifier” (emphasis added).

Table 1: Measure word use in Chinese customs data for exports, 2008

Quantity Measure	Meaning	Types of goods	Percent of export value
qiān kè, 千克	kilogram	grains, chemicals	40.5
tái, 台	machines	engines, pumps, fans	24.7
gè, 个	small items	golf balls, batteries, spark plugs	12.8
jiàn, 件	articles of clothing	shirts, jackets	6.6
shuāng, 双	paired sets	shoes, gloves, snow-skis	2.6
tiáo, 条	tube-like, long items	rubber tyres, trousers	2.5
mǐ, 米	meters	camera film, fabric	2.1
tào, 套	sets	suits of clothes, sets of knives	1.8
liàng, 辆	wheeled vehicles	cars, tractors, bicycles	1.4
sōu, 艘	boats	tankers, cruise ships, sail-boats	1.3
kuài, 块	chunky items	multi-layer circuit boards	0.7

is a high differentiation good while goods whose quantity is reported with a mass classifier are low differentiation goods. When integrated with the Rauch system, we indeed verify that almost all commodities traded on open exchanges are reported with mass classifiers—fully consistent with our view that mass classifiers identify low differentiation products.

For 2008, the dataset reports quantity using 36 different measure words. To illustrate the variety of measures used, table 1 reports a selection of measure words, the types of goods that use the measure word, and the percent of export value that is associated with products described by each measure word. In this table, qiān kè (千克) and mǐ, (米) are mass classifiers; the remaining measure words are count classifiers. The main point to be drawn from the table is that the nature of the Chinese language means that the reporting of differentiated goods, for example, automobiles, spark plugs and engines, takes place by reporting a number of items and the associated unique counter that is associated with that type of good. See appendix C.7 for additional examples of the Chinese quantity measures in our data.

Table 2 demonstrates the value added and power of our classification system in relation to that by Rauch. In the table, we integrate our classification of high versus low differentiation goods with that obtained by mapping HS06 product codes to Rauch’s original 4 digit SITC rev. 2 classification of differentiated, reference priced, and open exchange traded goods. The improvement is on at least two dimensions. First, our classification refines the class of differentiated goods in Rauch’s. From table 2 panel (a), we observe that 79.8 percent of observations are classified by Rauch as differentiated. Of these, only 48.6 percent (38.8/79.8) use count classifiers and are categorized as high differentiation under the CCHS approach. The picture is similar in panel (b), where observations are value weighted: of the 71.3 percent of the export value classified by

Table 2: Classification of goods: Integrating the insights from CCHS with Rauch

(a) Share of goods by classification: observation weighted

	Corsetti-Crowley-Han-Song (CCHS)		
	Low Differentiation / (Mass nouns)	High Differentiation / (Count nouns)	
Rauch (Liberal Version)			
Differentiated Products	41.1	38.8	79.8
Reference Priced	6.9	0.7	7.6
Organized Exchange	0.6	0.0	0.6
Unclassified [†]	10.5	1.5	12.0
	59.1	40.9	100.0

(b) Share of goods by classification: value weighted

	Corsetti-Crowley-Han-Song (CCHS)		
	Low Differentiation / (Mass nouns)	High Differentiation / (Count nouns)	
Rauch (Liberal Version)			
Differentiated Products	24.2	47.1	71.3
Reference Priced	9.1	2.8	11.9
Organized Exchange	2.0	0.0	2.0
Unclassified [†]	11.9	2.9	14.8
	47.2	52.8	100.0

Notes: Share measures are calculated based on Chinese exports to all countries including Hong Kong and the United States during periods 2000-2014. [†]: The “Unclassified” category refers to HS08 products that do not uniquely map to the SITC Rev. 2 classification of Rauch.

Rauch as differentiated, 66.1 percent (47.1/71.3) uses count classifiers.²⁵ Second, every good that Rauch categorizes as a commodity (an open-exchange traded good) is reported in the Chinese Customs Database with a mass classifier. This conforms with our prior that mass nouns are low differentiation goods.

A final, further benefit of our classification system is that we are able to provide a classification for goods that a concordance between HS06 and SITC Rev. 2 leaves unclassified under Rauch’s system. Note that around 12% percent of observations in panel (a) (and 14.8% of observations in panel (b)) do not uniquely map to a single Rauch category. They do according to our classification.²⁶

3 Data

To construct the dataset in this paper, we merge information from two datasets: (1) the Chinese Customs Database, i.e., the universe of annual import and export records for China from 2000 to 2014 and (2) annual macroeconomic data from the World Bank. Moreover, we turn to administrative data from Her Majesty’s Customs and Revenue (HMCR) in the UK to provide information about the currency of invoicing of Chinese exports so that we can place our results in context.

We begin with the Chinese Customs Database that reports detailed trade flows (quantities and values) at the firm-product-destination level. In addition to standard variables, such as the firm ID, an 8-digit HS code, the destination country and year²⁷, the database contains the Chinese measure word in which quantity is reported, an indicator of the form of commerce for tax and tariff purposes, and a categorization based on the registration type of the exporting firm.²⁸

Like other firm-level studies using customs databases, we use unit values as a proxy for prices.

²⁵We have constructed a concordance for all HS06 products as high differentiation or low differentiation by categorizing as high differentiation those HS06 product groups in which all HS08 products use a count classifier. This means that the CCHS classification of differentiated goods can be applied to the customs datasets for other countries.

²⁶The problem that arises is that the concordance of disaggregated HS06 product codes to (more aggregated) SITC Rev.2 involves 1-to-many or many-to-many mappings for 81 percent of concordance lines. Therefore, we cannot identify a unique mapping from HS06 to a Rauch-based SITC rev. 2 classification for 12% of observations in the Chinese Customs Database.

²⁷The database is available at the monthly frequency during the period 2000-2006 and annual frequency during the period 2007-2014. We aggregate the monthly data for 2000-2006 to the annual level in this study.

²⁸The form of commerce indicator records the commercial purpose of each trade transaction including “general trade,” “processing imported materials,” and “assembling supplied materials,” etc. The registration type variable contains information on the capital formation of the firm by 8 categories: namely state-owned enterprise, Sino-foreign contractual joint venture, Sino-foreign equity joint venture, wholly foreign owned enterprise, collective enterprise, private enterprise, individual business, and other enterprise. In our later analysis, we group three types of foreign-invested firms, namely wholly-foreign-owned enterprise, Sino-foreign contractual joint venture and Sino-foreign equity joint venture, into one category and dub it as “foreign invested enterprises.” We group minority categories such collective enterprise, individual business and other enterprise into one category and refer to them as “other enterprises.”

However, the rich information on forms of commerce, and Chinese measure words enables us to build more refined product-variety categories than prior studies have used. Specifically, we define the product identifier as an 8-digit HS code + a form of commerce dummy + a CCHS classification dummy.²⁹ The application of our product-variety definition generates 14,611 product-variety codes as opposed to the roughly 8,100 8-digit HS codes reported in the database. This refined product measure allows us to get a better proxy of prices for two reasons. First, the inclusion of the information on form of commerce helps to distinguish the subtle differences of goods being sold under the same 8-digit HS code.³⁰ Second, the extensive use of a large number of measure words as quantity reporting units makes unit values in Chinese data conceptually closer to transactions prices than unit values constructed with other national customs datasets.³¹

The Chinese Customs Database reports transactions denominated in US dollars. We calculate the price in the exporter’s currency (renminbi) by multiplying the unit value of dollar transactions with the annual renminbi-dollar rate.³²

4 Empirical Results by Product Type

In the rest of the paper, we present and discuss results obtained by applying our empirical framework to the Chinese Customs Database. In this section, we will first present our estimates on markup adjustment for the whole sample of Chinese exports. Then we will present estimates distinguishing between high and low differentiation goods and extend the analysis to cross-market supply elasticities. In the next section, we will redo our analysis by grouping firms according to their registration type, distinguishing private and public, as well as domestic and foreign ownership, and cross results with the classification by product.

To clarify the differences between our estimators and exchange rate pass-through estimators, as a reference benchmark, all our tables include estimates of the export price elasticity to the exchange rate (the complement of exchange rate pass through) obtained by following standard methodologies. This will allow us to quantify the relative contribution of the destination-specific

²⁹Firms in the Chinese Customs Database can produce the same product under two or more forms of commerce. Essentially, a good could be produced under different tax regulations depending on the exact production process used. In creating our form of commerce dummy, we generate a dummy variable equal to 1 if the transaction is “general trade” and 0 otherwise. The CCHS classification dummy equals 1 if the product is a high differentiation product and 0 if the product is a low differentiation product.

³⁰The primary reason why the number of product-varieties exceeds that of HS08 products is due to the addition of the form of commerce dummy.

³¹Important previous studies have constructed unit values (export value/export quantity) from data in which quantity is measured by weight (Berman, Martin and Mayer (2012)) or in a combination of weights and units (Amiti, Itskhoki and Konings (2014)).

³²Note that because our TPSFE estimator differences out the common components across destinations, using prices denominated in dollars with dollar-destination exchange rates versus using prices denominated in renminbi with renminbi-destination exchange rates in the estimation procedure yields exactly the same estimates.

markup elasticity (obtained by using our TPSFE estimator) to total export price adjustment.

Furthermore, we make our results comparable with recent leading studies in the literature on exchange rate pass through, by applying the TPSFE estimator following the same methodology as Gopinath, Itskhoki and Rigobon (2010) and condition our estimates on a price change. Specifically, we estimate all parameters *after* applying a data filter to the Chinese export data: for each product-firm-destination combination, we filter out absolute price changes in renminbi smaller than 5 percent. Thus, our pass-through estimates are based on S-period differences in prices, relative to the change in the exchange rate and other macro variables cumulated over the same S-period. The S-period interval defining a price change can vary within a firm-product-destination triplet and across these triplets. That is, for a single firm-product-destination triplet, we might observe S-period differences of, say, 2, 3, 4 or more years, within the 15 years included in our panel. We provide an example on how the price change filter is constructed and how trade patterns are subsequently formulated based on the price-change-filtered database in appendix C.4.

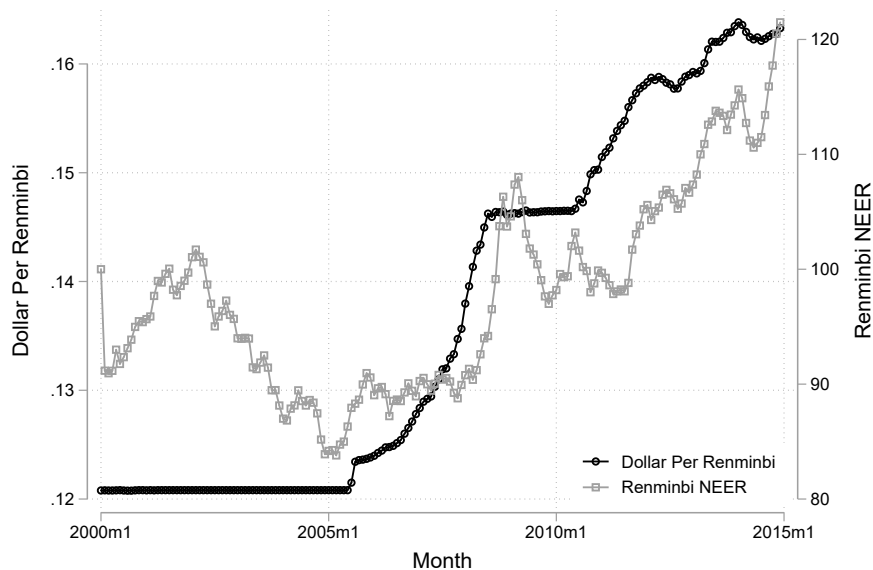


Figure 1: Renminbi Movements 2000-2014

We will report results separately for the subsamples corresponding to the two exchange rate regimes pursued by China, the fixed exchange rate regime of 2000-2005 and the managed float regime of the latter period. Figure 1 plots the bilateral movement of the renminbi against the US dollar, as well as China’s nominal effective exchange rate, over our entire sample period. As will be discussed in later sections, there is evidence that exporters’ pricing behavior differs across the two environments.

Throughout our analysis, we treat eurozone countries as a single economic entity and integrate

their trade flows in a single economic region.³³ In addition, we exclude exports to the US and Hong Kong to ensure comparability of our estimates across regimes.

4.1 Markup adjustments and incomplete pass through

Applying our estimator to our entire sample of exports (without distinguishing goods by their degree of differentiation), we find that, on average, destination-specific markup adjustments are moderate, and account for a non-negligible share of incomplete pass through into import prices. Their quantitative importance, however, increased after China abandoned its strict peg to the dollar in 2005. Since the degree of exchange rate pass through is relatively high, markup adjustments account for a non-negligible share of the incomplete pass through into import prices.

Estimation results from applying the ERPT estimator and our estimator to our entire sample (without distinguishing goods by their degree of differentiation) are shown in Table 3. Columns (1) and (2) in the table show ERPT estimates. In reading the results on these columns, it is important to keep in mind that we measure export prices in renminbi and bilateral exchange rates as renminbi per unit of foreign currency—a *low coefficient on the export price* elasticity in columns (1) and (2) means *a high pass through into import prices* in foreign (local) currency. Column (3) and (4) shows the TPSFE results.

Starting with the ERPT: as shown in the table, the elasticity of export prices (in renminbi) to bilateral exchange rates is low and stable across the two subsamples. On average, conditional on a price change, the renminbi price of Chinese exports responds to nominal bilateral exchange rate movements by 23% over the 2000-2005 period and 24% over 2006-2014 period. These estimates mean that pass through into import prices in local currency in destination markets is, on average, high and stable over time: it was about 77% in the years of China’s currency peg and essentially the same, 76%, in later years.

Note that the coefficients on the destination real GDP and the import share of GDP, meant to capture the export price response to factors specific to the destination market, have positive signs,

³³Specifically, we aggregate the export quantity and value at the firm-product-year level for 17 eurozone countries including Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Malta, Netherlands, Portugal, Slovakia, Slovenia and Spain. Latvia and Lithuania joined the eurozone in 2014 and 2015, respectively. We treat them as separate countries throughout our analysis.

Our results are robust to the inclusion and exclusion of small countries that adopted the euro in the later period of our sample. We performed two robustness checks. One excludes Slovenia, Cyprus, Malta, Slovakia and Estonia from the eurozone group and treats them as separate individual countries, resulting in an estimation sample of 159 destinations. Another excludes Slovenia, Cyprus, Malta, Slovakia and Estonia from the eurozone group and drops these five countries from our estimation sample, resulting in an estimation sample of 154 destinations. These two alternative estimation samples yield very similar results to our primary estimation sample (154 destinations) which integrates 17 eurozone countries together.

For macroeconomic series, we use the World Bank reported CPI index, bilateral exchange rates and import-to-GDP ratio for the euro area. We construct a “GDP constant local currency” measure for the eurozone using the reported “GDP constant US dollar (2010)” variable and the 2010 euro-dollar rate.

Table 3: Price and Markup Elasticities to Exchange Rates

	Price Elasticity (1-ERPT)		Markup Elasticity (Destination-specific)	
	(1)	(2)	(3)	(4)
	2000-2005	2006-2014	2000-2005	2006-2014
Bilateral nominal exchange rates	0.23*** (0.01)	0.24*** (0.01)	0.07*** (0.01)	0.11*** (0.01)
Destination CPI	0.09*** (0.02)	0.58*** (0.01)	-0.03* (0.02)	-0.00 (0.01)
Destination real GDP	0.41*** (0.03)	0.05*** (0.01)	-0.02 (0.02)	-0.01 (0.00)
Import-to-GDP ratio	0.22*** (0.01)	0.30*** (0.01)	0.01 (0.01)	0.05*** (0.01)
Number of Observations	1,076,815	4,863,196	1,076,815	4,863,196
Variation Used	516,552	3,050,928	1,072,775	4,824,344
Fixed Effects	No	No	TPSFE	TPSFE

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 154 destinations excluding Hong Kong and the United States. The “Price Elasticity” columns report estimates regressing S-period accumulated changes in renminbi unit values on S-period accumulated changes in nominal bilateral exchange rates and other macro-level control variables. The “Markup Elasticity” columns present estimates from our TPSFE estimator. Both the “Price Elasticity” and the “Markup Elasticity” columns are estimated based on the same estimation sample of filtered price changes following the procedure specified in appendix C.4. Note that constructing S-period time differenced variables will result in a smaller number of observations compared to fixed effect approaches as the initial year of each firm-product-destination triplet becomes a missing value when we take time differences. The bilateral exchange rate is defined as renminbis per unit of destination currency; an increase means an appreciation of the destination currency. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *.

as expected. Also, observe that the destination CPI has a sizeable, positive effect on export prices and that this increases substantially after the renminbi is unpegged from the US dollar.

To explain the difference between ERPT and our estimator, it is useful to decompose the price adjustment to the exchange rate into three components: (a) a general markup adjustment that is the same across all markets, (b) a destination-specific markup adjustment and (c) any change in marginal costs. In columns 1 and 2, our estimates of the price elasticity to the exchange rate combine movements in all these three components. In particular, the coefficient captures the average of the price elasticity to bilateral exchange rates across all markets. In contrast, our TPSFE estimator is designed to isolate the component under (b) the relative price adjustments to the relative exchange rate movements across markets, also averaged across all destinations. Under our identification condition, marginal costs do not enter the estimation. Hence the relative price adjustment is equivalent to the relative markup adjustment across destinations, i.e., the destination-specific adjustment of the markup.

The estimates in columns (3) and (4) are quite different from the ERPT estimates. Conditional on a price change in renminbi occurring at $t + s$, the average destination-specific markup changes by 7% of the cumulated bilateral exchange rate movement between t and $t + s$ during the dollar peg period (column 3). After the change in the exchange rate regime, as shown in column (4), the destination-specific markup response rises to 11% of the cumulated movement.

Comparing these with the point estimates of the ERPT, note that the adjustment in relative markups across destination accounts for about 1/3 of overall price adjustment (7% divided by 23%) in the first subsample, and for about 1/2 of it (11% divided by 24%) in the second. Thus our results suggest that, even if total pass through did not change, firms became considerably more active in adjusting their destination-specific markups after China abandoned its strict peg to the US dollar.³⁴

The differences in markup elasticities we detect across our subsamples are likely to reflect more than just the policy reform with the switch from a dollar peg to a managed float in China. They may stem from structural changes at the firm and market level, as well as from changes in the frequency and importance of cyclical (policy and technology) shocks at the national and global level that have occurred between the two time periods.³⁵

4.2 High versus low differentiation goods

We now turn to our results from disaggregating the sample according to our product classification. To introduce and motivate this step, we find it instructive to analyse markup adjustments by firms producing two products with different degree of differentiation. As case studies, we select canned tomato paste (measured in kilograms), as representative of low differentiation manufactured goods according to our CCHS classification, and wheeled tractors (measured with “liang”), as a high differentiation good. We visualize graphically the relationship between changes in relative markups and movements of relative exchange rates, using our destination-demeaned variables.

In figure 2, we plot the dispersion of markups across destinations for the top three exporters of tomato paste (upper panel) and wheeled tractors (lower panel) in 2007 and 2008. For each annual observation of a sale, we calculate the deviation of the sales price from its mean across destinations

³⁴In columns (3) and (4) we also estimate a tiny markup adjustment to the idiosyncratic component of local CPI growth over 2000-2005 (column 3) and no change in the later period (column 4). The difference in estimated coefficients on CPI in columns (1) versus (3) and (2) versus (4) arises because our approach removes the global trend in the exporter’s price associated with global CPI movements and isolates the local component.

³⁵The price elasticity provides different information relative to estimates of pass through that are made conditional on a specific shock hitting the economy – a point elaborated at length by [Corsetti, Dedola and Leduc \(2008\)](#). To wit: we would expect the price response to exchange rate movements to be quite different if the underlying shock is to productivity as opposed to monetary policy. Estimates of pass through conditional on a shock require methodologies, like VARs, suitable to identifying these shocks in isolation and tracing their effects on the exchange rate, export prices, and markups – see [Forbes, Hjortsoe and Nenova \(2017\)](#).

within the firm-product-year triplet (where sales price is the log unit value in renminbi), i.e. $wv_{ifdt} - \bar{wv}_{ift}$, and plot these deviations using different shapes (i.e., triangle, square, and circle) for each firm. The x-axis measures positive and negative deviations of the sales price from the mean value in 2007; the y-axis measures the deviations from the mean in 2008.³⁶ Any observation on the 45 degree line is a product whose relative markup in its destination d did not change between 2007 and 2008. Thus, a point lying on the 45 degree line at, say, 0.2 represents a product that was sold in some destination d at a 20% premium over the firm’s mean price in both 2007 and 2008. An observation plotted above the 45 degree line depicts a product-destination whose markup increased between 2007 and 2008 *relative* to the firm’s sales of the good in other destinations. Conversely, an observation plotted below the 45 degree line represents a product-destination that saw its relative markup fall.

We color-code each point representing a firm-product-destination triplet according to whether the destination’s currency appreciated or depreciated during 2007-2008 relative to the other destinations the firm was selling to. Red indicates relative appreciation, blue relative depreciation. Above and below the 45 degree line, we report the number of observations marked by red dots, corresponding to bilateral appreciations, in ratio to the number of observations marked by blue dots corresponding to depreciations.

These graphs illustrate three key results from our analysis. First, the relative markups for many firm-product-destination triplets, measured in the producer’s currency, change from year to year. Second, the low differentiation good, tomato paste, exhibits less dispersion in its markups across destinations than the high differentiation good, wheeled tractors. Third and most importantly, for high differentiation goods, appreciation of the destination market currency relative to the renminbi is associated with an increase in relative markups—red dots are denser above the 45 degree line—, while depreciation of the destination market currency is associated with a decrease in relative markups. No such clear pattern emerges between relative markup changes and relative currency changes for the low differentiation good, tomato paste.

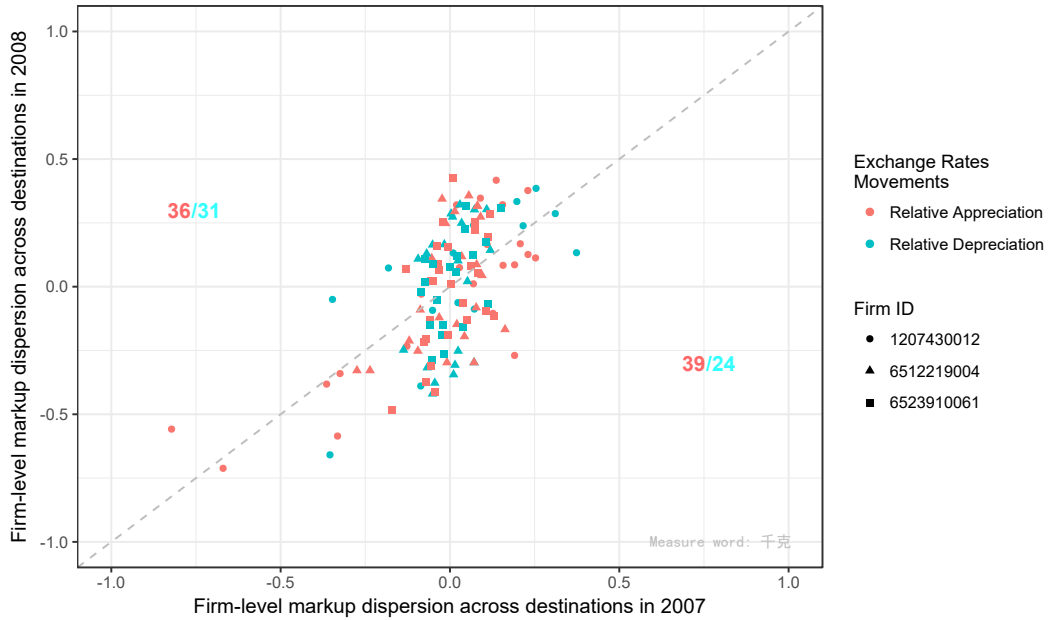
4.2.1 Markup elasticities using the CCHS product classification

In line with our discussion of the two case studies above, our econometric analysis documents significant differences in both pass through and markup elasticities across high and low differentiation goods. Overall, product differentiation appears to be a good proxy for market power, validating the usefulness of our linguistics-inspired product classification.

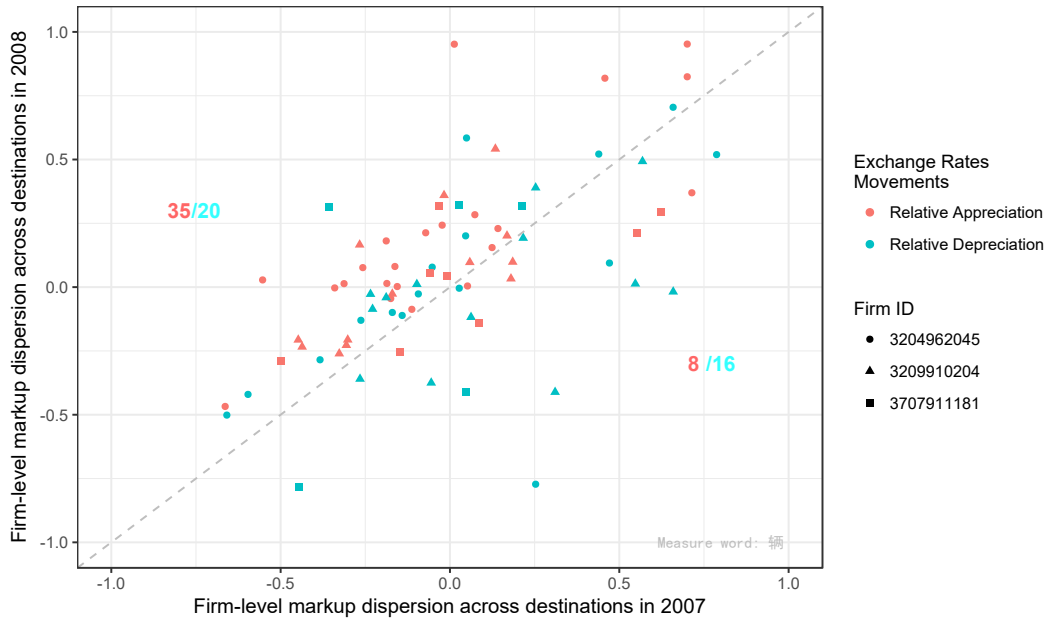
Results are shown in table 4. For comparison, the first two columns of the table reproduce the

³⁶The magnitude of price dispersion within a year across destinations for wheeled tractors is of the same order of magnitude as that found in European automobile prices in an important study of international market segmentation by Goldberg and Verboven (2001).

Figure 2: Markup dispersion across destinations for top three firms in 2007 and 2008



Example 1: Canned Tomato Paste (a low differentiation product)



Example 2: Wheeled Tractors (a high differentiation product)

Note: Firm-level markup dispersion for tomato paste (HS20029010) and wheeled tractors (HS87019011) is calculated as the deviation from the mean log unit value, denominated in RMB, across destinations at the firm-product-year level, i.e., $uv_{ifdt} - \bar{uv}_{ift}$. For this figure, we begin with a balanced panel of firm-product-destination observations for two consecutive years, 2007 and 2008, and plot the observations of markup dispersion for the top three firms based on the number of observations in the constructed balanced panel. Red observations are for destinations whose currency appreciated relative to the renminbi between 2007 and 2008 while blue observations are for destinations whose currencies depreciated.

key results from table 3, average export price and markup elasticities for the universe of Chinese exports. The remaining four columns report results for the subsamples of high and low differentiation goods. The first row refers to the dollar peg period, the second row to the more recent period in the sample. In both subperiods, the renminbi prices and markups of high differentiation goods respond more to bilateral exchange rates movements, implying lower ERPT, than low differentiation goods. For low differentiation goods, pricing-to-market actually plays no role during the dollar peg, and only a moderate role after the strict peg is abandoned.

Focusing on quantitative results: during the fixed exchange rate period (row 1), we have already seen that the markup elasticity over all goods is relatively small, 7% (column (2)). The results in the table show that this low average estimate conceals important differences across types of good. For CCHS high differentiation exports, the markup elasticity is as high as 14%—for low differentiation goods it is as low as 2% and statistically indistinguishable from zero.

In the period of the managed float of the renminbi (second row of table 6), markup elasticities are considerably higher. For high differentiation goods, the export price elasticity rises from 25 to 32% (and exchange rate pass through correspondingly falls to $1-.32=.68$); the markup elasticity rises from 14 to 20%. Note that the markup adjustment to the exchange rate accounts for two-thirds of the price elasticity ($0.20/0.32$). For low differentiation goods, the markup elasticity is smaller but becomes significantly positive, at 6%. This accounts for one-third of the adjustment in renminbi prices, estimated at 19%.

Table 4: Price and Markup Elasticities by CCHS Classification

	All		High Differentiation		Low Differentiation		n. of obs
	Price	Markup	Price	Markup	Price	Markup	
2000 – 2005	0.23*** (0.01)	0.07*** (0.01)	0.25*** (0.02)	0.14*** (0.02)	0.22*** (0.02)	0.02 (0.01)	1,076,815
2006 – 2014	0.24*** (0.01)	0.11*** (0.01)	0.32*** (0.01)	0.20*** (0.01)	0.19*** (0.01)	0.06*** (0.01)	4,863,196

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 154 destinations excluding Hong Kong and the United States. The “Price Elasticity” columns report estimates regressing S-period accumulated changes in renminbi unit values on S-period accumulated changes in nominal bilateral exchange rates and other macro-level control variables. “Markup Elasticity” columns present estimates from our TPSFE estimator. Both “Price Elasticity” and “Markup Elasticity” columns are estimated based on the same estimation sample of filtered price changes following the procedure specified in appendix C.4. Destination CPI, real GDP and M/GDP controls are included in each regression; related estimates are omitted for conciseness. The bilateral exchange rate is defined as renminbis per unit of destination currency; an increase means an appreciation of the destination currency. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *.

4.2.2 Integrating the CCHS product descriptions with UN end-use categories

Firms selling directly to consumers typically engage in branding and advertising campaigns to a much larger extent than firms selling intermediate products. Insofar as consumption goods producers are successful in making their products less substitutable with other products or product varieties, markets for consumption goods should be less competitive than markets for intermediates. Thus, we may expect markup elasticities to be higher for consumption goods than for intermediates.

To gain further insight on how the intensity of market competition can impact pricing by firms, we now split our data combining our CCHS classification with the classification of consumption goods and intermediates under the UN's Broad Economic Categories (BEC).³⁷ Results are shown in Table 5.

In line with our argument above, the price-setting behaviour is quite different across the two types of goods. The estimated markup elasticities are higher for consumption goods than for intermediates, both in the dollar peg years and the managed float period. During the dollar peg era, the markup elasticity is sizeable for consumption goods (0.10, row 1, column (2)), but not statistically significant for intermediate goods (row 2, column (2)). Observe that consistent with our results in table 3, after China abandoned the dollar peg, the magnitudes of markup elasticities increase for both consumption goods (0.20, row 3, column (2)) and intermediates (0.05, row 4, column (2)).

Within each end-use category, we can still detect higher markup elasticities for high differentiation relative to low differentiation goods. During the dollar peg period (top panel of the table), markup elasticities are significantly different from zero only for high differentiation goods—consumption goods exhibit the largest value (0.17, row 1, column (4)), followed by intermediates (0.14).

Under the managed float, markup elasticities are positive and significant for all types of goods, pointing to extensive pricing-to-market. Our estimated elasticity actually peaks for high differentiation consumption goods (0.32, row 4 column (4)), almost three times the value for high differentiation intermediates (0.12, row 3 column (6)). The markup elasticities are lower for low differentiation goods, and quite close for consumption and intermediate goods (0.08 and 0.05, rows 4 and 5, column (4)).

³⁷ The UN's BEC classifies all internationally traded goods according to their end-use. The most disaggregated classification available in BEC Rev. 4 maps HS06 products into end-use categories of consumption goods, intermediate inputs, and capital equipment. For our analysis, all HS08 products into the Chinese Customs Database are assigned the end-use of their corresponding HS06 code.

Table 5: Price and Markup Elasticities by BEC Classification

Category	All		High Differentiation		Low Differentiation		n. of obs
	Price	Markup	Price	Markup	Price	Markup	
2000 – 2005							
Consumption	0.25*** (0.02)	0.10*** (0.02)	0.29*** (0.02)	0.17*** (0.02)	0.19*** (0.03)	0.02 (0.02)	426,462
Intermediate	0.23*** (0.02)	0.03 (0.02)	0.22*** (0.06)	0.14*** (0.05)	0.24*** (0.02)	0.01 (0.02)	294,929
2006 – 2014							
Consumption	0.33*** (0.01)	0.20*** (0.01)	0.44*** (0.01)	0.32*** (0.01)	0.16*** (0.02)	0.08*** (0.02)	1,756,214
Intermediate	0.21*** (0.01)	0.05*** (0.01)	0.34*** (0.06)	0.12*** (0.04)	0.19*** (0.01)	0.05*** (0.01)	1,593,591

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 154 destinations excluding Hong Kong and the United States. The “Price Elasticity” columns report estimates regressing S-period accumulated changes in renminbi unit values on S-period accumulated changes in nominal bilateral exchange rates and other macro-level control variables. “Markup Elasticity” columns present estimates from our TPSFE estimator. Both “Price Elasticity” and “Markup Elasticity” columns are estimated based on the same estimation sample of filtered price changes following the procedure specified in appendix C.4. Destination CPI, real GDP and M/GDP controls are included in each regression; related estimates are omitted for conciseness. The bilateral exchange rate is defined as renminbis per unit of destination currency; an increase means an appreciation of the destination currency. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *.

During the dollar peg, a slightly larger markup elasticity for low differentiation consumption goods (8%) relative to low differentiation intermediates (5%) lends support to the idea that, even within this group of manufactured goods, at least some firms producing consumption goods are successful in acquiring market power. Furthermore, all groups of products experience a rise in markup elasticities with the adoption of the managed float, except for high differentiation intermediate goods, whose markup elasticities are not statistically different during the peg and the managed float period.

As already pointed out, our results are informative on the extent to which incomplete exchange rate pass through can be attributed to a destination-specific markup adjustment, as opposed to common markup adjustment across markets and changes in production costs. During the managed float period, the estimated ERPT into import prices in local currency for high differentiation consumption goods is only 56% (corresponding to an export-price elasticity of 0.44). This is far lower than most estimates using micro firm-level data. In our findings, three-quarters of this

incomplete ERPT can be attributed to destination-specific markup adjustments (0.32/0.44, row 3, column (4)/column (3)).

For high differentiation intermediates, pass through into import prices is higher, 66% (1-0.34, row 4, column (3)); however, the fraction of the incomplete pass through due to destination-specific markup adjustments is far smaller—about one-third (0.12/0.34, row 4, column (4)/column (3)). The same is true for intermediate inputs that are low differentiation. For these goods, ERPT is 81% (1-0.19, row 4, column (5)), and the destination-specific markup adjustment explains only about one-quarter of the incomplete pass through.³⁸

4.2.3 The CCHS and Rauch classification systems compared

According to the Rauch classification system, products traded on open exchanges (OE) are generally regarded as commodities whose prices are expected to fluctuate with global supply and demand. Reference price (RP) products are list-price goods: firms producing them compete somewhat directly by supplying at the price published in some industry-trade publication. These goods are thought to offer a very limited scope for market power in pricing. Conversely, differentiated goods are defined as goods for which prices are not publicly negotiated—which indicate limited direct competition among firms and greater scope for charging markups. As argued above, our linguistics based classification allows us to refine the Rauch classification by distinguishing differentiated goods using two finer categories, and by classifying goods for which there is not enough information about pricing.

To highlight the contribution of our product-feature-based classification system relative to Rauch (1999)’s market-structure based classification, we now integrate the two in our empirical analysis. Results are shown in table 6.

³⁸The trade policy implications of market power in intermediates characterised by high differentiation or “customisability” are significant; see, e.g., the model by Antràs and Staiger (2012).

Table 6: Price and Markup Elasticities by Rauch Classification

Category	All		High Differentiation		Low Differentiation		n. of obs
	Price	Markup	Price	Markup	Price	Markup	
2000 – 2005							
Differentiated Products	0.22*** (0.01)	0.09*** (0.01)	0.25*** (0.02)	0.14*** (0.02)	0.20*** (0.02)	0.04** (0.02)	815,223
Organized Exchange	0.60*** (0.06)	0.02 (0.05)	-	-	0.62*** (0.06)	0.02 (0.05)	11,925
Reference Priced	0.23*** (0.03)	0.09** (0.04)	0.05 (0.16)	0.26** (0.12)	0.24*** (0.04)	0.08* (0.04)	88,959
2006 – 2014							
Differentiated Products	0.22*** (0.01)	0.12*** (0.01)	0.32*** (0.01)	0.20*** (0.01)	0.14*** (0.01)	0.07*** (0.01)	3,944,681
Organized Exchange	1.02*** (0.07)	-0.05 (0.05)	-	-	1.03*** (0.07)	-0.05 (0.05)	27,235
Reference Priced	0.43*** (0.02)	0.11*** (0.02)	0.14 (0.10)	0.16* (0.09)	0.45*** (0.02)	0.10*** (0.02)	366,974

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 154 destinations excluding Hong Kong and the United States. The “Price Elasticity” columns report estimates regressing S-period accumulated changes in renminbi unit values on S-period accumulated changes in nominal bilateral exchange rates and other macro-level control variables. “Markup Elasticity” columns present estimates from our TPSFE estimator. Both “Price Elasticity” and “Markup Elasticity” columns are estimated based on the same estimation sample of filtered price changes following the procedure specified in appendix C.4. Destination CPI, real GDP and M/GDP controls are included in each regression; related estimates are omitted for conciseness. The bilateral exchange rate is defined as renminbis per unit of destination currency; an increase means an appreciation of the destination currency. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *.

Not surprisingly, our estimates of markup elasticities are zero for goods traded in organized exchanges, which in our classification are treated as low differentiation goods (rows 2 and 5, column (2)). However, our estimator detects a positive elasticity for goods that are ‘reference priced’ in Rauch (rows 3 and 6, column (2)), and unveils an increase in market power across the two currency regimes.

The most important takeaway from table 6 is, however, that the estimated markup elasticity of “differentiated” goods according to the Rauch classification, 12% in the later sample, is an average of very different elasticities for high and low differentiation goods, 20% and 7% respectively.

4.3 A Comparative Assessment of Estimators

In this section, we compare the TPSFE estimator with commonly used estimating procedures in the literature.³⁹ Table 7 reports estimated markup elasticities using seven alternative estimating procedures. To illustrate the importance of the selection problem, we first note that the seven estimation procedures in table 7 would all generate exactly the same estimates if the panel of firm-product-destination customs transactions were balanced, i.e., if all firms exported all products to all destinations in all time periods. In practice, the panel of customs data is very unbalanced. Unbalancedness in the set of a firm’s markets will generate bias in markup elasticities if a firm’s market selection is endogenous to changes in exchange rates and marginal cost. In table 7, the distinct estimators yield very different values of the markup elasticity; this indicates that endogenous market selection is a quantitatively important problem.

The first piece of evidence comes from comparing estimates from the first two columns of table 7. The first column presents the TPSFE estimator. The second column attempts to estimate the markup elasticity by running a regression of destination-demeaned variables on destination fixed effects rather than trade pattern fixed effects. The observation that the estimates in column (2) are much closer to zero than those in column (1) suggests that market participation is not random, but endogenous to changes in local market conditions.⁴⁰ This piece of evidence underscores the value of using the TPSFE estimator to properly specify a firm’s trade pattern when market selection is endogenous to the variable of interest. Again, if there were no endogenous market selection at the firm-product level, i.e., the set of destinations to which a firm-product pair exports were the same across all time periods, or if firms’ trade patterns were random, estimates of (1) and (2) would be exactly the same.

In columns (3) and (4), we quantify the degree of endogenous selection bias by exploiting a subtlety in the application of Correia (2017)’s high-dimensional fixed effects estimator (henceforth HDFE) using firm-product-time + destination (fpt, d) (column (3)) versus firm-product-destination + time (fpd, t) fixed effects (column (4)) in an unbalanced panel. The analytical difference between these two distinct HDFEs, (fpt, d) versus (fpd, t) (reported in expression (39) in appendix B.2), serves as natural measure of the degree of the endogenous selection bias. As shown in columns (3) and (4) of table 7, the markup elasticities estimated using (ifd, t) fixed effects can be 40-50% higher compared to those estimated using (ift, d) effects, suggesting a non-negligible endogenous selection effect.

While the empirical difference in applying these two estimators may be large or small depending

³⁹Analytical details on all the estimators in a comparative perspective are presented in the subsections B.1 – B.3.

⁴⁰In the estimation specification of table 7, we have included four variables as proxies for changes in local market conditions, namely bilateral exchange rates, local CPI, destination real GDP and import-to-GDP ratio. Under the this specification, the estimated coefficient of bilateral exchange rates can be biased if the market selection is related in any of the four variables.

on the market structure and the underlying shocks (e.g., exchange rates versus tariff changes), we show that the correct data partition is firm-product-time + destination (ift, d) rather than firm-product-destination + time (ifd, t) if controlling for unobserved marginal costs is the primary concern.⁴¹

Finally, in the last three columns of table 7, we report estimates of the markup elasticity obtained from three different variants of a regression in which different time dummies are applied to time-differenced data. These columns demonstrate the sensitivity of estimators of the markup elasticity to the correct partitioning of the data when the panel is endogenously unbalanced. As explained in the section 2, there are two key elements that matter in estimating markups by exploiting destination variation to control for marginal costs: (a) the correct data partition or fixed effects and (b) the correct way to implement the (correct) data partition. Although there are equivalent procedures that implement the correct data partition, some estimation procedures implement a data partition that is not equivalent to the TPSFE estimator; potentially, these may lead to biased estimates of markup elasticities. By way of example, in table 7 we find considerably higher estimates of these elasticities using the procedure that first takes S-period differences and then applies different sets of destination and time fixed effects.⁴²

⁴¹Examples in applying (ifd, t) fixed effects in levels include Berman, Martin and Mayer (2012) and Chatterjee, Dix-Carneiro and Vichyanond (2013). However, note that main objectives of these two studies are not the same as ours. Berman, Martin and Mayer (2012) already controlled for the estimated productivity in their specification. Therefore, the bias may be small even if the dominated estimator is applied.

⁴²We discuss this in detail in subsections B.2 and B.3.

Table 7: Comparison across Estimators

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	n. of obs
	TPSFE	No Trade Pattern	HDFE (ift, d)	HDFE (ifd, t)	S-Diff + (t)	S-Diff + (ifd, t)	S-Diff + (ift, d)	
Destination Demean	Yes	Yes	No	No	No	No	No	
S-period Difference	No	No	No	No	Yes	Yes	Yes	
Fixed Effects	Firm Product Trade Pattern ($TP_{ifd, D_{ift}}$)	Destination (d)	(ift, d)	(ifd, t)	Time (t)	(ifd, t)	(ift, d)	
2000 – 2014								
All Products	0.098*** (0.005)	0.021*** (0.000)	0.073*** (0.005)	0.116*** (0.007)	0.198*** (0.007)	0.246*** (0.016)	0.140*** (0.010)	5,940,011
High Differentiation	0.184*** (0.009)	0.017*** (0.000)	0.123*** (0.008)	0.202*** (0.013)	0.312*** (0.012)	0.486*** (0.025)	0.248*** (0.016)	2,430,061
Low Differentiation	0.056*** (0.007)	0.024*** (0.000)	0.042*** (0.006)	0.071*** (0.009)	0.129*** (0.009)	0.121*** (0.021)	0.084*** (0.012)	3,509,950
2006 – 2014								
All Products	0.106*** (0.006)	0.021*** (0.000)	0.092*** (0.007)	0.138*** (0.009)	0.219*** (0.008)	0.268*** (0.018)	0.155*** (0.011)	4,863,196
High Differentiation	0.196*** (0.010)	0.016*** (0.000)	0.160*** (0.012)	0.241*** (0.015)	0.363*** (0.013)	0.557*** (0.029)	0.274*** (0.018)	1,951,051
Low Differentiation	0.064*** (0.007)	0.024*** (0.000)	0.054*** (0.008)	0.085*** (0.011)	0.136*** (0.010)	0.119*** (0.023)	0.095*** (0.013)	2,912,145

Note: Each cell reports the estimated markup elasticity to exchange rates from the estimation method specified on top of each column. Destination CPI, real GDP and M/GDP controls are included in all estimation methods; related estimates are omitted for conciseness. Each row indicates a different subsample. Within a row, all methods are applied based on the same sample. The number of observations in the last column corresponds to Stage 8 of the data cleaning procedure specified in appendix C.4. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *.

4.4 Cross Market Supply Elasticity

We conclude this section by investigating the flip side of the markup elasticity to exchange rates, that is, firms’ cross market supply elasticity. The question we ask is to what extent, in response to exchange rate movements, do firms reallocate their output across markets as they adjust their own markups in different destinations. Table 8 presents the estimates obtained by applying the method developed at the end of section 2, together with the results from a naïve regression of relative quantities on relative prices, conditional on the trade pattern fixed effects.

Starting from the naïve regression, the column (1) of the table shows that a 1% increase in relative prices is statistically associated with a 0.7% *decline* in relative quantities. The naïve regression simply reveals that, in equilibrium, firms sell relatively small quantities in markets where they set relatively high prices.⁴³

The result from the naïve regression contrasts sharply with the results from our CMSE estimator. For the managed float regime, over the 2006-2014 period (table 8, row 2), our estimated cross market supply elasticity is positive and equal to 1.51 (row 2, column (2)): a one percent increase in the relative markup (driven by the exchange rate) is associated with 1.5 percent change in the relative quantity across destinations. In relative terms, exports *rise* in destinations where firms also increase markups in response to a local currency appreciation. What is especially significant here is the change in the sign of the regression coefficient when we apply our method. The CMSE is designed to isolate the relative quantity adjustments across destinations *caused* by markup adjustments to exchange rate movements.

A positive slope coefficient from the CMSE estimator confirms that our TPSFE approach is able to isolate the demand-side effects of exchange rate fluctuations. The main idea underlying the development of our statistical procedure consists of exploiting relative movements in bilateral exchange rates to trace shifts in the relative demand across a firm’s markets—by projecting relative prices/markups on exchange rates. These projections are then used to trace out a firm’s relative “willingness to supply” across markets.

The most important finding in this table consists of the sharp difference in estimated CMSEs across high and low differentiation goods. Over the 2006-2014 period, the estimated CMSE is very low for high differentiation goods, 0.83 (row 2, column 4), consistent with a view that firms exporting high differentiation products respond to destination-specific exchange rate movements by adjusting markups, rather than by letting the foreign-currency price move substantially with the exchange rate (which would effect a larger adjustment in quantities). In contrast, the estimated CMSE for low differentiation goods is quite high: a one percent increase in the relative markup is associated with 2.47% increase in the relative quantity supplied. Altogether, these results un-

⁴³This could reflect low levels of competition/high market power, in turn pointing to higher barriers to entry, or fixed costs as an important component of trade costs.

derscore important heterogeneity in price-setting and quantity responses between high and low differentiation goods.

We know already that exporters from China engaged in only modest amounts of pricing-to-market during the years of the fixed exchange rate regime in our sample. Indeed, over these years, bilateral exchange rate movements are a quantitatively important predictor of destination-specific markup adjustments only for high differentiation goods—with a sizeable 0.14 markup elasticity (see table 4). For these goods, our estimated CMSE is quite high, 2.57. All together, these results suggest that, during the strict peg period, firms responded to bilateral exchange rate movements with modest markup adjustments—they rather aggressively pursued openings for higher profits through large increases in relative quantities, i.e., a 2.57% increase in the relative quantity supplied associated with a 1 percent increase in the relative markup.

Table 8: Cross Market Supply Elasticity by CCHS Classification

	All		High Differentiation		Low Differentiation		n. of obs
	Naive Reg.	CMSE	Naive Reg.	CMSE	Naive Reg.	CMSE	
2000 – 2005	-0.71*** (0.00)	4.09*** (0.82)	-0.74*** (0.00)	2.57*** (0.49)	-0.68*** (0.00)	†	1,076,815
2006 – 2014	-0.70*** (0.00)	1.51*** (0.16)	-0.73*** (0.00)	0.83*** (0.12)	-0.68*** (0.00)	2.47*** (0.43)	4,863,196

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 154 destinations excluding Hong Kong and the United States. The “Naive Reg” column is estimated using specification (11). The “CMSE” column is estimated based on equations (9) and (10). † indicates that the t-statistic of the bilateral exchange rate in the first stage is smaller than 2.58. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *.

Table 9: Cross Market Supply Elasticity by BEC Classification (2006 – 2014)

Category	All		High Differentiation		Low Differentiation		n. of obs
	Naive Reg.	CMSE	Naive Reg.	CMSE	Naive Reg.	CMSE	
Consumption	-0.71*** (0.00)	0.54*** (0.11)	-0.77*** (0.00)	0.23** (0.09)	-0.63*** (0.00)	1.92*** (0.59)	1,756,214
Intermediate	-0.71*** (0.00)	2.92*** (0.73)	-0.74*** (0.01)	1.33 (0.86)	-0.70*** (0.00)	3.27*** (0.90)	1,593,591

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 154 destinations excluding Hong Kong and the United States. The “Naive Reg” column is estimated using specification (11). The “CMSE” column is estimated based on equations (9) and (10). † indicates that the t-statistic of the bilateral exchange rate in the first stage is smaller than 2.58. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *.

We conclude with additional evidence on the extent and importance of international market segmentation and market power. Table 9 reports our CMSE estimates for high and low differentiation

goods by Broad Economic Categories. At one extreme we have highly differentiated consumption goods: a very low quantity substitution across destinations suggests that the markets for these goods are highly segmented. At the other extreme, quantity substitution is quite high and markets appear quite integrated for low differentiation exports, especially of intermediates.

5 Empirical analysis by product and firm types

The intense competition that Chinese imports have brought to high income countries has spawned research into how this enhanced global competitive pressure has influenced corporates' decisions to upgrade their product mix (Bernard, Jensen and Schott (2006)), innovate (Bloom, Draca and Van Reenen (2016)), lay off workers (Autor, Dorn and Hanson (2013), Pierce and Schott (2016)), and outsource to lower wage markets (Pierce and Schott (2016)). Business people and economists speak of the problem of “the China price,” the low price of Chinese merchandise that exporters from other markets and domestic import-competing firms must match if they want to survive. In section 4.2, we provided evidence that strategic pricing-to-market and markup adjustments are more prominent in the markets for high differentiation goods, especially consumption goods, while quantitatively less pronounced in the markets for low differentiation manufactured goods with higher degrees of competition. We now dig deeper into the Chinese Customs Database, and examine how to square our results so far with the evolving identity of Chinese exporters.

The Chinese economy is widely understood to be a hybrid in which competitive, market-oriented private firms operate alongside large, state-owned enterprises (SOEs).⁴⁴ Looking at exports, the picture is actually more complex. Quantitatively, export activity is dominated by firms that are wholly foreign owned or are Sino-foreign joint enterprises—the leading types in a group that we label foreign-invested enterprises (FIEs).

Reflecting their ownership/type, firms are likely to have different cost structures and face different demand elasticities. First, SOEs and FIEs are believed to have relatively easy access to capital, but are likely to differ in the extent to which they rely on imported intermediates in production. Conversely, private firms are widely seen as facing tighter financing constraints and, relative to FIEs, a lower level of integration with global supply chains. Second, the average size of a firm also differs across these groups; private enterprises are smaller on average, which likely reflects a high rate of entry by young firms. Third, being more integrated in supply chains, FIEs may engage in transfer pricing. In light of these considerations, we might expect SOEs, FIEs and private firms to endogenously end up producing different products, using different production processes, and possibly targeting different markets. This prompts us to ask whether a firm's

⁴⁴See Hsieh and Song (2015) and Wu (2016) for analyses of the inter-relations of firms and the state in the Chinese economy and Hale and Long (2012) on the importance of inward FDI into China.

registration type contribute to explaining observable differences in pricing, markup adjustments and cross-destination quantity adjustments.

5.1 The evolution of exports by private, state owned and foreign investment firms in China

In figure 3, we lay out some basic facts about the evolution of different types of firms among Chinese exporters. In the Chinese Customs Database, firms report their registration type in one of the following eight categories: state-owned enterprise, Sino-foreign contractual joint venture, Sino-foreign equity joint venture, wholly foreign owned enterprise, collective enterprise, private enterprise, individual business, and “other” enterprise. We combine Sino-foreign contractual joint ventures, Sino-foreign equity joint ventures, and wholly foreign owned enterprises into a single category - foreign invested enterprises (FIEs). Firms with other ownership structures, including collectives, individual businesses, and “other” enterprises, are lumped together under the descriptor “Other” enterprises.

A well-known fact is the extraordinary rate of entry into export activity by private enterprises. This is apparent in the top panel of the figure. From being a small and neglectable group in 2000, the number of private enterprises directly exporting goods from China to the rest of the world rose to over 200,000 by 2014.⁴⁵ Perhaps less known and understood, however, is the economic weight of a different category of exporters *from* China, the foreign-invested enterprises (FIEs), also highlighted by our figure. After a slow and steady rise between 2000 and 2006, their number stabilized at about 75,000 firms—dwarfing the presence of state-owned enterprises (SOEs). Indeed, in spite of the attention paid to them by the media, there were only 10,000 registered SOEs at the start of our sample period. This number gradually fell over time, as successive policy initiatives favored their privatization, or led some of them to exit from foreign markets (top panel, figure 3).

The key message from the top panel of figure 3 is reinforced by the evidence on export values and shares by different types of firms, shown in the bottom panel. By export value and share of total exports, the most important single group of exporters from China is that of foreign-invested enterprises. In 2014, the value of their exports was over US \$1 trillion (bottom left panel of figure 3). Over the period, exports from China that originated from firms that are wholly or partially owned by foreigners fluctuated between 45 and 58% of China’s total exports.⁴⁶

⁴⁵At the start of our sample period, export activity was highly regulated in China with most rights to export held by SOEs—only a very limited number of private enterprises were able to export directly. The result of this was that in the earlier years post-2000 private enterprises desiring to export their merchandise exported through SOEs.

⁴⁶The importance of foreign involvement in Chinese exports has previously been documented by [Koopman, Wang and Wei \(2014\)](#). Based on an accounting framework methodology and product-level trade flows, they show that 29.3 percent of Chinese export value comes from foreign, rather than domestic Chinese, value-added. This is not

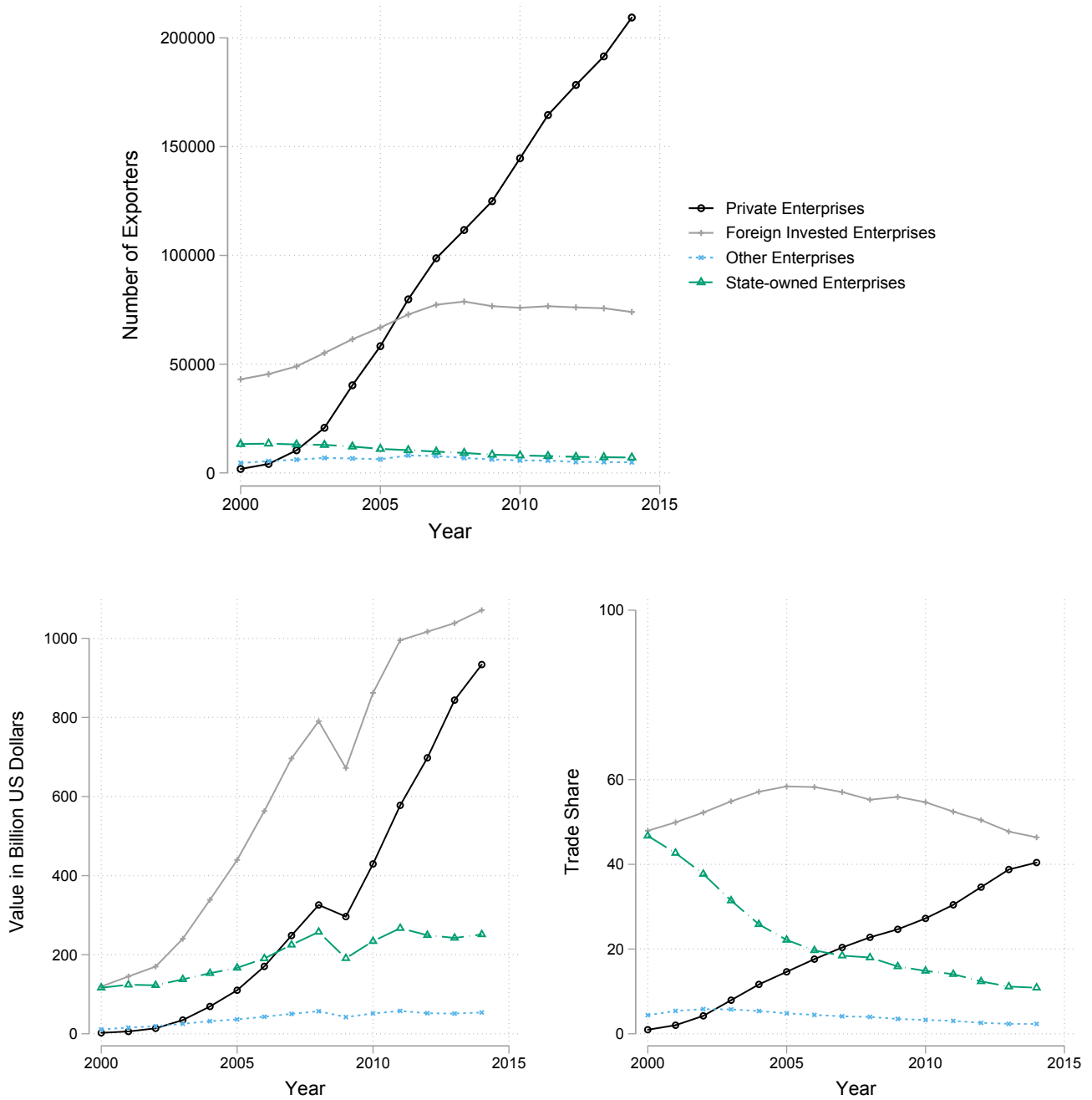


Figure 3: The changing face of Chinese exporters, 2000-2014

Note: Calculations based on the universe of all exporters from the customs database of China. Three types of foreign invested enterprises are reported in our dataset, namely wholly foreign owned enterprises (coded as “4”), sino-foreign joint ventures by jointed equity (coded as “3”) and by contractual arrangements that specify the division of tasks and profits (coded as “2”). The last type is quantitatively small in firm number and trade values.

Conversely, the weight of SOEs, which were essentially at par with FIEs in 2000, declined dramatically from 2000 to 2007 and then settled into a slow and steady negative trend (bottom left panel, figure 3). This is clear evidence that the role of SOEs in foreign trade has been far less dynamic than that of other types of firms. However, the diminishing weight of SOEs in foreign trade has been more than made up by private firms—reflecting both entry of new firms into export markets and privatization of SOEs. By the end of the sample, private firms account for a striking 40% of Chinese exports. We stress nonetheless that this large shift in export shares between SOEs and private firms has not (so far at least) dented the share of exports by FIEs, which has remained quite stable over our sample.

The question is whether, against this evolution in the number of exporters and export shares by ownership, there are significant differences in strategic pricing.

5.2 Markup and supply elasticities by firms' type

Evidence on price, markup and supply elasticities by firm type is presented in table 10, where we focus on the sample 2006-2014. In this period, relative to other Chinese exporters, foreign-invested enterprises (FIEs) stand out in that, across destination markets, they make larger adjustments to their renminbi export prices (0.49), have moderately elastic markups (0.21), and have an inelastic within-firm cross market supply elasticity (CMSE) (see table 10, row 2, columns (1), (2) and (4)). The high estimate of the Chinese export price elasticity of 0.49 implies that the ERPT into *import* prices in foreign currency is relatively low (51%), reflecting that these firms are more actively pursuing local currency price stabilization than other groups of firms. Notably, markup adjustment accounts for two fifths (0.21/0.49) of this incomplete pass through into import prices.

Relative to FIEs, the export price response to exchange rates by SOEs is smaller, 0.32 (see row 1, column (1) of table 10), implying a much higher pass through into *import* prices, as high as 68%. While SOEs make similar markup adjustments compared to FIEs in absolute terms, the share of markup adjustment to incomplete pass through is higher (0.22/0.32 versus 0.21/0.49). Like FIEs, SOEs have an extremely low cross market supply elasticity, 0.47 (row 1, column (4)). This evidence together suggests that both FIEs and SOEs are endowed with a high degree of market power which enables them to exploit market segmentation and strategically price-to-market.

The picture is totally different for private enterprises. On average, these firms adjust their export prices far less than either SOEs or FIEs—by a mere 1 percent in response to a 10 percent appreciation (see row 3, column (1) of table 10). Of this, a modest 40 percent is due to a tiny, yet statistically significant, markup adjustment by destination (0.04/0.10). Pass through into foreign *import* prices is as high as 90 percent. What is truly extraordinary is the within-firm cross market

inconsistent with our estimates; our complementary contribution is to document foreign engagement based on *ownership* of exporting firms, rather than through the origin of the value-added content of exported goods.

supply elasticity: for private firms, a one percent increase in the relative markup caused by a bilateral exchange rate appreciation leads to a 4.7 percent increase in the relative quantity sold in that destination. This is evidence that, on average, Chinese private firms aggressively chase profit opportunities across destination markets by expanding quantities, but make only small markup adjustments in response to destination-specific currency movements.⁴⁷

Table 10: Pricing Strategies by Firm Registration Types (2006 – 2014)

	Price Elasticity	Markup Elasticity	Naive Reg.	CMSE	n. of obs
Full Sample					
State-owned Enterprises	0.32*** (0.02)	0.22*** (0.02)	-0.70*** (0.00)	0.47*** (0.15)	644,385
Foreign Invested Enterprises	0.49*** (0.01)	0.21*** (0.02)	-0.69*** (0.00)	0.22 (0.14)	1,053,734
Private Enterprises	0.10*** (0.01)	0.04*** (0.01)	-0.70*** (0.00)	4.72*** (0.94)	3,010,176
High Differentiation					
State-owned Enterprises	0.46*** (0.03)	0.39*** (0.03)	-0.69*** (0.00)	0.38*** (0.14)	283,697
Foreign Invested Enterprises	0.53*** (0.02)	0.35*** (0.02)	-0.69*** (0.00)	0.09 (0.12)	446,663
Private Enterprises	0.16*** (0.01)	0.09*** (0.01)	-0.75*** (0.00)	2.54*** (0.53)	1,153,886
Low Differentiation					
State-owned Enterprises	0.24*** (0.02)	0.13*** (0.02)	-0.71*** (0.00)	0.62* (0.35)	360,688
Foreign Invested Enterprises	0.47*** (0.02)	0.14*** (0.02)	-0.69*** (0.00)	0.24 (0.28)	607,071
Private Enterprises	0.07*** (0.01)	0.02*** (0.01)	-0.67*** (0.00)	8.42** (3.34)	1,856,290

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 154 destinations excluding Hong Kong and the United States. The “Naïve Reg” column is estimated using specification (11). Estimation methods for the “Price Elasticity” and “Markup Elasticity” columns are the same as in previous tables. The “Naïve Reg.” column is estimated using specification (11). The “CMSE” column is estimated based on equations (9) and (10). † indicates that the t-statistic of the bilateral exchange rate in the first stage is smaller than 2.58. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *.

The second and third panels of table 10 break down the estimates by firm type, distinguishing between high and low differentiation goods. Two key results stand out. First, within each class

⁴⁷This type of highly responsive substitution of export value (p^*q) across markets has also been identified in the context of destination-specific tariff increases and product-level trade flows by Bown and Crowley (2006) and Bown and Crowley (2007). In the trade flow and tariff literature, it is referred to as “trade deflection.” A similar cross-destination supply response of capital flows has been identified by Giordani, Ruta, Weisfeld and Zhu (2017).

of firms, the number of exporters of either high and low differentiation goods is large (see the number of observations for each sample in column (5)): there is no apparent specialization by firm type. This means that the different pricing behavior noted in our comments about the top panel of table 10 cannot be attributed to a different typology of goods produced and exported across groups. Second, for each type of firm, results are consistent with our findings in section 4. Markup elasticities are higher for high differentiation goods than for low differentiation goods. Cross market supply elasticities are correspondingly lower for the former and higher for the latter group of goods.

To better appreciate the meaning and potential implications of our results for theory and policy, consider the response of different types of firms and products to an idiosyncratic appreciation of a foreign currency, say, the Mexican peso, relative to the renminbi. For private firms exporting goods with low differentiation, the depreciation of the renminbi leads to relatively high yet not complete pass through into the peso-denominated prices (1-.07 =93 percent, from row 9, column (1) of table 10), and a small (2%) increase in the markup. This small increase in the markup accounts for less than one third (0.02/0.07) of the change in export prices. In other words, Chinese private enterprises exporting low differentiation goods respond to an appreciation of the local currency by letting the local-currency price of their products fall and expanding their sales rather aggressively—adjustments to markups are minor. In our estimates, indeed, a 1% increase in the relative markup for the good in Mexico is met with an 8.4% increase in the relative quantity sold by the firm to Mexico (row 9, column (4) of table 10). For private firms exporting high differentiation goods, the exchange rate pass through into peso prices is somewhat lower, about 84% (1-.16). Yet, markup adjustment is not appreciably higher, 9% instead of 2%. Accounting for possibly different cost structures (due, for example, to the higher share of imported intermediate inputs in high differentiation goods), the strategic pricing behavior is quite comparable among private firms, regardless of whether they sell high or low differentiation goods.

Relative to private firms, for SOEs and FIEs pass through into import prices is considerably lower and markup adjustment is considerably higher. For high differentiation exports from China, ERPT into peso prices is around 50% (1-.46 = 54% for SOEs and 47% for FIEs, rows 4 and 5, column (1) of table 10). SOEs and FIEs clearly prefer to raise their markups, by 39% for SOEs and 35% for from FIEs (rows 4 and 5, column (2)), rather than expand sales. The estimated cross-market supply elasticities are indeed very small (0.38 for SOEs and 0.09 for FIEs). A similar picture emerges from our analysis of SOEs and FIEs exporting low differentiation goods, although, not surprisingly, markup adjustment is lower.

Overall, our results provide striking evidence that, on average, SOEs and FIEs exporting from China have significant power in setting prices—they exploit this power by letting their markups increase significantly with a foreign currency appreciation. This points to a strategic decision by

firms to exploit market segmentation and keep destination markets separated: Averaged over all exported goods, there is only a 0.47% (SOEs) increase and no change for (FIEs) in the relative quantity sold in Mexico for a 1% increase in the relative markup. Although these results may in part capture transfer pricing motivated by profit shifting practices, it remains true that the divide relative to Chinese private firms is large: over our sample period, private firms have aggressively pursued local market expansions, rather than exploiting opportunities to raise their prices.

A comment is in order concerning our findings. In comparison to FIEs and SOEs, private enterprises are on average smaller, reflecting the high rate of entry documented at the beginning of this section. Hence, a substantial share of them are likely at an early stage of their life cycle in which growth can be expected to have precedence over the exploitation market power. Interpreting our results from a cross-sectional perspective is likely to overestimate heterogeneity—once they achieve their equilibrium size, private firms may well exercise monopoly power and behave like FIEs and SOEs.⁴⁸

5.3 Pricing behavior under the dollar-renminbi peg

The results discussed so far suggest that SOEs and FIEs wield substantial market power. Was this also the case in the first part of our sample, when the renminbi was pegged to the US dollar (2000-2005)? An analysis of pricing, markups and the CMSE during this period suggests a different story.

Our evidence for the dollar peg period is shown in Table (11). Across all types of firms in the table, adjustments of export prices to currency movements were modest—ERPT into foreign import prices was as high as 76 percent (1-0.24), 77 percent (1-0.23), and 88 percent (1-0.12) for SOEs, FIEs, and private firms, respectively (rows 1-3, column (1)).

Both FIEs and SOEs have smaller markup adjustments (rows 2 and 3, column (2)) in response to exchange rates during the dollar peg era, relative to the later period. Indeed, these firms appear to have been following a strategy of aggressively expanding quantity: a 1 percent increase in the relative markup in a destination is associated with a 3 percent increase in the relative quantity for SOEs and a roughly 8 percent increase for FIEs. In contrast to the managed floating period, private firms made significant markup adjustments of 9% (row 3, column (2)), the largest among all groups. We conjecture this is because the sunk cost for private firms to obtain an export license in China was relatively high in early 2000s. With only a limited number of private firms directly engaged in international trade, the level of competition among them was less severe. Consistent with our conjecture, we find a low cross market elasticity (2.26, row 3 column (4)) for this period relative to that during the managed float (4.72, row 3 column (4) in the previous table).

⁴⁸We leave to future research a refinement of our analysis along these lines.

Table 11: Pricing Strategies by Firm Registration Types (2000 – 2005)

	Price Elasticity	Markup Elasticity	Naive Reg.	CMSE	n. of obs
Full Sample					
State-owned Enterprises	0.24*** (0.02)	0.08*** (0.02)	-0.74*** (0.00)	2.99*** (0.81)	519,674
Foreign Invested Enterprises	0.23*** (0.03)	0.05** (0.02)	-0.59*** (0.01)	7.81**† (3.63)	268,598
Private Enterprises	0.12*** (0.04)	0.09*** (0.03)	-0.76*** (0.01)	2.26** (1.15)	216,374
High Differentiation					
State-owned Enterprises	0.28*** (0.02)	0.15*** (0.02)	-0.77*** (0.01)	1.97*** (0.54)	234,928
Foreign Invested Enterprises	0.20*** (0.04)	0.10*** (0.03)	-0.63*** (0.01)	5.82*** (2.18)	123,590
Private Enterprises	0.15** (0.06)	0.14*** (0.04)	-0.82*** (0.01)	1.14 (1.08)	85,859
Low Differentiation					
State-owned Enterprises	0.21*** (0.02)	0.03 (0.02)	-0.71*** (0.01)	6.32† (4.93)	284,746
Foreign Invested Enterprises	0.26*** (0.03)	0.01 (0.03)	-0.56*** (0.01)	17.72† (40.86)	145,008
Private Enterprises	0.10** (0.05)	0.07** (0.03)	-0.72*** (0.01)	3.56† (2.50)	130,515

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 154 destinations excluding Hong Kong and the United States. The “Naïve Reg” column is estimated using specification (11). Estimation methods for the “Price Elasticity” and “Markup Elasticity” columns are the same as in previous tables. The “Naïve Reg.” column is estimated using specification (11). The “CMSE” column is estimated based on equations (9) and (10). † indicates that the t-statistic of the bilateral exchange rate in the first stage is smaller than 2.58. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *.

Important insights can be gained by looking at the second and third panels in the table, which break down our estimates by types of goods traded. Comparing SOEs exporting high and low differentiation goods (rows 4 and 7, column (2)), we see that the result in the first panel is entirely due to a significant markup elasticity for high differentiation products. For these products, around one-half of this incomplete pass through is due to markup adjustments (0.15/0.28, from row 4, columns (1) and (2)). For low differentiation exports by SOEs, we detect no markup adjustment (row 7, column (2)). The story is similar for FIEs: the average markup elasticity is 0.09 across all goods, but this is essentially driven by the high differentiation goods (with an elasticity of 0.10, row 5 column (2)).

6 Conclusions

The increasing availability of large, multi-dimensional, administrative datasets of firms is enabling researchers to explore new questions into the operation of the global economy, as well as to re-examine classic questions in new ways. In this paper, we have proposed a new empirical strategy that exploits administrative data on exporters in order to examine both markup and quantity adjustments by firms to currency movements. While our motivation for this paper is an analysis of exports, the methodology we developed can be applied to other contexts in which producers sell to multiple markets/buyers and may price discriminate across them.

Our first contribution in this paper is a framework to estimate the export price markup elasticity and the cross-market supply elasticity to the exchange rate. We showed that the TPSFE estimator is capable of controlling for a firm’s time-vary marginal cost at the product level, even when the panel of data is endogenously unbalanced. More importantly, we derive an identification condition showing that our estimator can remain unbiased even in the presence of destination-specific production costs—so long as these are not systematically correlated with the exchange rate in growth rates.

Markup adjustments can be expected to vary with the degree of competition in a market. To explore this issue, we have constructed a new, general classification of Harmonized System products aided by a specific feature of Chinese linguistics and information on traded quantities reported to Chinese Customs Authorities. We use a linguistic classification of Chinese measure words, or quantity measures, to classify HS products into high and low differentiation categories and use this to proxy for market power. In conjunction with our TPSFE estimator, this classification allows us to document striking differences in empirical elasticities between high and low differentiation goods. Moreover, it adds value to existing classification systems such as Rauch (1999) and the UN’s Broad Economic Categories.

Our empirical results document significant heterogeneity across categories of goods. We find that firms exporting high differentiation goods from China make moderate but significant destination-specific adjustments to markups in response to movements of bilateral exchange rates—markup adjustments account for up to three quarters of incomplete exchange rate pass through into import prices. In contrast, producers of commodities and low differentiation goods make minuscule or no adjustments. These different elasticities are mirrored (inversely) by cross market adjustments in quantities exported.

Altogether, these results tell us that the nature of the good matter enormously in gauging the extent of international market segmentation and firms’ market power across markets. A high degree of pricing-to-market can be expected for highly differentiated goods, for which the cross-market substitution of quantity by firms is very low. In contrast, firms producing low dif-

ferentiation intermediates appear more similar to commodity producers, in their inconsequential use of destination-specific markup adjustments and their highly elastic cross-market substitution of supply. Relatedly, we find much higher destination-specific markup adjustment among State Owned Enterprises and Foreign Investment Enterprises (on average larger and endowed with more market power) than among private firms.

This empirical evidence provides an important diagnostic for the development of open economy models featuring a richer and more detailed account of firms' dynamics and strategies. In related work ([Corsetti, Crowley and Han \(2018\)](#)) we assess the extent to which leading models of export pricing and dynamics can account for the qualitative patterns and magnitudes of the elasticities we find in the data. Preliminary results yield a sharp message: while leading models cannot match our evidence on their own, a multi-country syncretic model—accounting for both multilateral competition among producers, and vertical interactions between exporters and local distributors—can.

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A General Relationships (Model Free)

A.1 The separation of marginal cost and markup

We start deriving a general expression of a firm's profit-maximizing price. Please note that variables in the following derivation are in levels rather than logarithms. Write:

$$\max_p q(p, \xi)p - c[q(p, \xi), \zeta] \quad (12)$$

The firm takes its demand function, $q(p, \xi)$, and cost function, $c[q(p, \xi), \zeta]$, as given and maximises its profit by choosing its optimal price p . ξ and ζ are exogenous demand and supply function shifters respectively.

The first order condition of the firm is given by

$$\frac{\partial q(p, \xi)}{\partial p} p + q(p, \xi) = \frac{\partial c[q(p, \xi), \zeta]}{\partial q(p, \xi)} \frac{\partial q(p, \xi)}{\partial p} \quad (13)$$

From this equation, we can derive the optimal price as

$$p^* = \frac{\varepsilon(p^*, \xi)}{\varepsilon(p^*, \xi) - 1} mc[q(p^*, \xi), \zeta] \quad (14)$$

where $\varepsilon(p, \xi) \equiv -\frac{\partial q(p, \xi)}{\partial p} \frac{p}{q(p, \xi)}$, $mc[q(p, \xi), \zeta] \equiv \frac{\partial c[q(p, \xi), \zeta]}{\partial q(p, \xi)}$.

A.2 The equilibrium relationship between quantity and price under pure supply versus demand shocks

Proposition 1. *If changes in price and demand are solely driven by shocks to the supply side, the following expression holds*

$$\frac{d \log(q^*)}{d \log(p^*)} = -\varepsilon(p^*, \xi) \quad (15)$$

Proof.

$$\begin{aligned} d \log(q(p^*(\xi, \zeta), \xi)) &= \frac{1}{q(p^*(\xi, \zeta), \xi)} dq(p^*(\xi, \zeta), \xi) \\ &= \frac{1}{q(p^*(\xi, \zeta), \xi)} \left(\frac{\partial q(p^*(\xi, \zeta), \xi)}{\partial p^*(\xi, \zeta)} dp^*(\xi, \zeta) + \frac{\partial q(p^*(\xi, \zeta), \xi)}{\partial \xi} d\xi \right) \end{aligned} \quad (16)$$

$$d \log(p^*(\xi, \zeta)) = \frac{1}{p^*(\xi, \zeta)} dp^*(\xi, \zeta) \quad (17)$$

Substituting equation 17 into 16 and applying the condition $d\xi = 0$ completes the proof. \square

Proposition 2. *If changes in price and demand are solely driven by shocks to the demand side, the following expression holds*

$$\frac{d \log(q^*)}{d \log(p^*)} = \frac{\varphi_q(p^*, \xi)}{\varphi_p(\xi, \zeta)} - \varepsilon(p^*, \xi) \quad (18)$$

where $\varphi_q(p^*, \xi) \equiv \frac{\partial q(p^*, \xi)}{\partial \xi} \frac{\xi}{q(p^*, \xi)}$ and $\varphi_p(\xi, \zeta) \equiv \frac{\partial p^*(\xi, \zeta)}{\partial \xi} \frac{\xi}{p^*(\xi, \zeta)}$

Proof.

$$\begin{aligned} d \log(q(p^*(\xi, \zeta), \xi)) &= \frac{1}{q(p^*(\xi, \zeta), \xi)} \left(\frac{\partial q(p^*(\xi, \zeta), \xi)}{\partial \xi} d\xi + \frac{\partial q(p^*(\xi, \zeta), \xi)}{\partial p^*(\xi, \zeta)} dp^*(\xi, \zeta) \right) \\ &= (\varphi_q(p^*, \xi) - \varepsilon(p^*, \xi) \varphi_p(\xi, \zeta)) \frac{d\xi}{\xi} \end{aligned} \quad (19)$$

$$\begin{aligned} d \log(p^*(\xi, \zeta)) &= \frac{1}{p^*(\xi, \zeta)} dp^*(\xi, \zeta) \\ &= \frac{1}{p^*(\xi, \zeta)} \left(\frac{\partial p^*(\xi, \zeta)}{\partial \xi} d\xi \right) \\ &= \varphi_p(\xi, \zeta) \frac{d\xi}{\xi} \end{aligned} \quad (20)$$

□

B Estimator

In this section, we derive the identification condition of our TPSFE estimator and discuss the endogenous selection problem that is present when estimating markup elasticities using a four dimensional (firm-product-destination-time) customs database. Subsection B.1 derives the identification condition for the TPSFE estimator in a balanced panel. Subsection B.2 discusses bias due to endogenous selection of markets and compares the identification condition of our estimator with that of two commonly used alternatives. In subsection B.3, we simulate a set of numerical examples to illustrate the bias that may arise from an endogenously unbalanced panel and discuss various cases where the marginal cost is destination-specific. Subsection B.5 gives a structural interpretation of the required identification condition.

B.1 Balanced Panel

In a balanced panel, we can write the unbiasedness condition as

$$\frac{1}{n^I n^F n^D n^T} \sum_i \sum_f \sum_d \sum_t (\tilde{m}c_{ifdt} - \frac{1}{n^I n^F n^T} \sum_i \sum_f \sum_t \tilde{m}c_{ifdt}) (\tilde{e}_{dt} - \frac{1}{n^T} \sum_t \tilde{e}_{dt}) = 0 \quad (21)$$

Where n^j denotes for the number of indices in dimension $j \in \{i, f, d, t\}$; \bar{x}_j is defined as the mean of variable x taken over all dimensions other than j ; and

$$\begin{aligned} \tilde{m}c_{ifdt} - \frac{1}{n^I n^F n^T} \sum_i \sum_f \sum_t \tilde{m}c_{ifdt} &= mc_{ifdt} - \frac{1}{n^D} \sum_d mc_{ifdt} \\ &\quad - \frac{1}{n^I n^F n^T} \sum_i \sum_f \sum_t mc_{ifdt} + \frac{1}{n^I n^F n^D n^T} \sum_i \sum_f \sum_d \sum_t mc_{ifdt} \\ &= mc_{ifdt} - \bar{m}c_{ift} - (\bar{m}c_d - \bar{m}c) \\ &= \psi_{ifdt} - \bar{\psi}_{ift} - (\bar{\psi}_d - \bar{\psi}) \end{aligned}$$

$$\begin{aligned} \tilde{e}_{dt} - \frac{1}{n^T} \sum_t \tilde{e}_{dt} &= e_{dt} - \frac{1}{n^I n^F n^T} \sum_i \sum_f \sum_t e_{dt} \\ &\quad - \frac{1}{n^I n^F n^D} \sum_i \sum_f \sum_d e_{dt} + \frac{1}{n^I n^F n^D n^T} \sum_i \sum_f \sum_d \sum_t e_{dt} \\ &= e_{dt} - \bar{e}_t - (\bar{e}_d - \bar{e}) \end{aligned}$$

Therefore, we can rewrite equation (21) as

$$\frac{1}{n^I n^F n^D n^T} \sum_i \sum_f \sum_d \sum_t (\psi_{ifdt} - \bar{\psi}_d - \bar{\psi}_{ift} + \bar{\psi})(e_{dt} - \bar{e}_t - \bar{e}_d + \bar{e}) = 0 \quad (22)$$

Since exchange rates are not firm and product specific in a balanced panel, we can simplify equation (22) as:

$$\frac{1}{n^D n^T} \sum_d \sum_t \left[\frac{1}{n^I n^F} \sum_i \sum_f (\psi_{ifdt} - \bar{\psi}_d - \bar{\psi}_{ift} + \bar{\psi}) \right] (e_{dt} - \bar{e}_t - \bar{e}_d + \bar{e}) = 0 \quad (23)$$

or write as

$$\frac{1}{n^D n^T} \sum_d \sum_t (\bar{\psi}_{dt} - \bar{\psi}_t - \bar{\psi}_d + \bar{\psi})(e_{dt} - \bar{e}_t - \bar{e}_d + \bar{e}) = 0 \quad (24)$$

Note that, as a deviation term, the compositional error must satisfy

$$\frac{1}{n^D} \sum_d \psi_{ifdt} = 0 \quad \forall ift \quad (25)$$

With this relationship, we can write (24) as

$$\frac{1}{n^D n^T} \sum_d \sum_t (\bar{\psi}_{dt} - \bar{\psi}_d)(e_{dt} - \bar{e}_d) = 0 \quad (26)$$

B.2 Unbalanced panel

In this subsection, we discuss a subtle, yet important difference in applying destination fixed effects to control for marginal costs in an endogenously unbalanced panel.

B.2.1 A parsimonious factor decomposition to illustrate the endogenous selection problem

To illustrate the problem raised by the endogenous selection of destination markets, we find it useful to decompose the markup and marginal cost components into collections of factors that vary along the four key dimensions i, f, d, t . Omitting coefficients (i.e., β_i , etc.) in front of the

factors for conciseness, and accounting for all possible combinations among factors, we can write:

$$\begin{aligned}
\mu_{ifdt} &= \mathcal{F}_i + \mathcal{F}_f + \mathcal{F}_d + \mathcal{F}_t \\
&+ \mathcal{F}_{if} + \mathcal{F}_{id} + \mathcal{F}_{it} + \mathcal{F}_{fd} + \mathcal{F}_{ft} + \mathcal{F}_{dt} \\
&+ \mathcal{F}_{fdt} + \mathcal{F}_{idt} + \mathcal{F}_{ift} + \mathcal{F}_{ifd} \\
&+ \mathcal{F}_{ifdt} \\
\overline{m\bar{c}}_{ift} &= \mathcal{C}_i + \mathcal{C}_f + \mathcal{C}_t \\
&+ \mathcal{C}_{if} + \mathcal{C}_{it} + \mathcal{C}_{ft} \\
&+ \mathcal{C}_{ift}
\end{aligned} \tag{27}$$

Equation (27) captures all possible factors driving the markup and the (common-across-destinations) cost components. Demand factors include \mathcal{F}_d and \mathcal{F}_{id} , which could be interpreted as destination-specific tastes for all goods and for good i , respectively. Firm-level supply factors include \mathcal{C}_f and \mathcal{C}_{ft} . Time-varying factors common to all firms (in our application, GDP growth and CPI inflation in the exporting country, etc.) are captured by \mathcal{F}_t . The bilateral nominal exchange rate between the origin and the destination country d is accounted for by the factor \mathcal{F}_{dt} , which also includes macro variables such as CPI and GDP growth in the destination country d .

Panels of highly disaggregated firm-product-destination-time customs data are inherently unbalanced: frequently, the set of destinations served by a firm changes; arguably this occurs endogenously in response to exchange rate movements. Shifts in a firm's trade pattern naturally correspond to the firm's decision to discontinue sales in a market where the currency is too weak for its exports to be 'competitive' (vice versa for entry). This implies that observability of an $ifdt$ price is likely to be correlated with movements of the bilateral exchange rate \mathcal{F}_{dt} and the unobserved marginal cost components.

To see the estimation problem raised by endogenous selection of markets, consider a standard practice in empirical studies of nominal exchange rate pass through.⁴⁹ Usually, the first step in specifying ERPT models consists of taking a time difference. Time differencing is motivated by the fact that the series of nominal exchange rates or CPI indices cannot be directly compared across countries: the logged time difference, a growth rate, is instead comparable across destinations. When the objective of the estimation is to identify the export price markup elasticity, however, time differencing as an initial step is highly problematic. The selection of observations into the unbalanced, time-differenced panel depends on changes in bilateral exchange rates \mathcal{F}_{dt} and the unobserved marginal cost, $\overline{m\bar{c}}_{ift}$. The change in the price in destination d is only observed when

⁴⁹An advantage of using nominal exchange rates and CPI rather than the real exchange rate is that the nominal variables approach does not implicitly assume a relationship between nominal exchange rates and the relative CPI ratio.

the firm continues to sell the product in d in both periods, t and $t + s$. As already mentioned, this is less likely to occur when the producer’s currency has appreciated substantially relative to the local d currency—the producer may be endogenously ‘priced out’ of the market in d . *After* time differencing, introducing firm-product fixed effects to control for marginal cost will be ineffective relative to the goal of identifying the parameter of interest because the two components, cost and the exchange rate, are not orthogonal in time differences.

For the case of S-period time differencing conditional on ifd , this implies:

$$\begin{aligned}
\Delta_{s|ifd}p_{ifdt} &= \Delta_{s|ifd}\mathcal{F}_t + \Delta_{s|ifd}\mathcal{C}_t \\
&+ \Delta_{s|ifd}\mathcal{F}_{it} + \Delta_{s|ifd}\mathcal{F}_{ft} + \Delta_{s|ifd}\mathcal{F}_{dt} + \Delta_{s|ifd}\mathcal{C}_{it} + \Delta_{s|ifd}\mathcal{C}_{ft} \\
&+ \Delta_{s|ifd}\mathcal{F}_{fdt} + \Delta_{s|ifd}\mathcal{F}_{idt} + \Delta_{s|ifd}\mathcal{F}_{ift} + \Delta_{s|ifd}\mathcal{C}_{ift} \\
&+ \Delta_{s|ifd}\mathcal{F}_{ifdt}
\end{aligned} \tag{28}$$

where $\Delta_{s|j}x_{j,t} \equiv x_{j,t} - x_{j,t-s} \forall j \in \{f, i, f, d, fd, id, if, ifd\}$.

In other words, taking time differences changes the dimensions along which unobserved variables vary—making it impossible to control for them in later stages. By changing the panel dimension along which components of the firm-product marginal cost ($\Delta_{s|ifd}\mathcal{C}_t, \Delta_{s|ifd}\mathcal{C}_{it}, \Delta_{s|ifd}\mathcal{C}_{ft}, \Delta_{s|ifd}\mathcal{C}_{ift}$) vary, taking the S-period difference within a firm-product-destination introduces the possibility of a bias due to a non-zero correlation between changes in cost components, and factors that are destination and time specific $\Delta_{s|ifd}\mathcal{F}_{dt}$, e.g., destination-specific bilateral exchange rates. We provide a simulated example in [B.3.1](#).

In comparison, the first stage of our TPSFE estimator yields:

$$\tilde{p}_{ifdt} = \tilde{\mathcal{F}}_d + \tilde{\mathcal{F}}_{id} + \tilde{\mathcal{F}}_{fd} + \tilde{\mathcal{F}}_{dt} + \tilde{\mathcal{F}}_{fdt} + \tilde{\mathcal{F}}_{idt} + \tilde{\mathcal{F}}_{ifd} + \tilde{\mathcal{F}}_{ifdt} + \psi_{ifdt} \tag{29}$$

where $\tilde{x}_{ifdt} \equiv x_{ifdt} - \frac{1}{n^D} \sum_d x_{ifdt} \forall x \in \{p_{ifdt}, \mu_{ifdt}, mc_{ifdt}, \psi_{ifdt}\}$. Clearly, the demeaning process differences out all the factors that are not destination-specific, including the firm-product time-varying marginal cost. If any destination-specific marginal cost components are present, destination demeaning will subtract out the average marginal cost across all destinations at the firm-product-time level and yield a term ψ_{ifdt} , reflecting any production cost differences across sets of varieties (e.g., compositional differences) sold in different destination markets under the same product code for the same firm in a particular time period.

B.2.2 The identification condition of our proposed estimator under an endogenously unbalanced panel

We now prove that our proposed estimator requires a similar identification condition as the balanced panel case. For our proposed estimator, the identification condition can be written as

$$\frac{1}{n_{IFDT}} \sum_i \sum_f \sum_d \sum_t (\widetilde{m}c_{ifdt, D_{ift}} - \frac{1}{n_{dD}^{IFT}} \sum_{ift \in IFT_{dD}} \widetilde{m}c_{ifdt, D_{ift}}) (\widetilde{e}_{dt, D_{ift}} - \frac{1}{n_{dD}^{IFT}} \sum_{ift \in IFT_{dD}} \widetilde{e}_{dt, D_{ift}}) = 0 \quad (30)$$

where

$$\begin{aligned} \widetilde{m}c_{ifdt, D_{ift}} &\equiv mc_{ifdt} - \frac{1}{n_{ift}^D} \sum_{d \in D_{ift}} mc_{ifdt} \\ \widetilde{e}_{dt, D_{ift}} &\equiv e_{dt} - \frac{1}{n_{ift}^D} \sum_{d \in D_{ift}} e_{dt} \end{aligned}$$

D_{ift} is the set of destinations to which a firm-product-time triplet exports; and the number of destinations in this set is defined as $n_{ift}^D \equiv |D_{ift}|$. Similarly, IFT_{dD} denotes the set of firm-product-time triplets for a trade pattern dD and n_{dD}^{IFT} represents the number of firm-product-time triplets following that trade pattern.

Unlike the balanced panel case, the destination average of the exchange rate is now firm, product and time specific, depending on the set of destinations D_{ift} , i.e.,

$$\left(\bar{e}_{D_{ift}} \equiv \frac{1}{n_{ift}^D} \sum_{d \in D_{ift}} e_{dt} \right) \neq \left(\bar{e}_t \equiv \frac{1}{n_t^{IFD}} \sum_{ifd \in IFD_t} e_{dt} \right)$$

Throughout our analysis, we use capital letters in the subscript to characterise the scope of variability of the variable. For instance, the D in $\bar{e}_{D_{ift}}$ indicates the variability of $\bar{e}_{D_{ift}}$ is restricted to the sets of destinations D . Although $\bar{e}_{D_{ift}}$ could take firm-product-time specific values, the choices are not unrestricted; the values that $\bar{e}_{D_{ift}}$ can take are limited to the available sets of destinations D . As such, the variation of $\bar{e}_{D_{ift}}$ is not unique to each firm-product-time triplet. Rather, ift triplets that export to the same set of destinations D would need to share the same \bar{e}_D .

Define

$$\begin{aligned} \bar{\psi}_{IFT_{dD}} &\equiv \frac{1}{n_{dD}^{IFT}} \sum_{ift \in IFT_{dD}} \psi_{ifdt} \\ \bar{e}_{IFT_{dD}} &\equiv \frac{1}{n_{dD}^{IFT}} \sum_{ift \in IFT_{dD}} e_{dt} \end{aligned}$$

Note that

$$\bar{e}_{IFT_D} = \frac{1}{n_D^{IFT}} \sum_{ift \in IFT_D} \bar{e}_{D_{ift}} = \frac{1}{n_{dD}^{IFT}} \sum_{ift \in IFT_{dD}} \bar{e}_{D_{ift}}$$

which means the last term in the second parentheses of (30) can be expressed as

$$\frac{1}{n_{dD}^{IFT}} \sum_{ift \in IFT_{dD}} \tilde{e}_{dt, D_{ift}} = \bar{e}_{IFT_{dD}} - \bar{e}_{IFT_D} \quad (31)$$

Moreover, the following relationship holds

$$\tilde{\psi}_{ift, D_{ift}} \equiv \psi_{ift} - \frac{1}{n_{ift}^D} \sum_{d \in D_{ift}} \psi_{ift} = \psi_{ift} = \tilde{m}c_{ift, D_{ift}} \quad (32)$$

Using (31) and (32), condition (30) can be simplified to an expression similar to (22):

$$\frac{1}{n^{IFTD}} \sum_i \sum_f \sum_d \sum_t (\psi_{ift} - \bar{\psi}_{IFT_{dD}}) (e_{dt} - \bar{e}_{D_{ift}} - \bar{e}_{IFT_{dD}} + \bar{e}_{IFT_D}) = 0 \quad (33)$$

To simplify expression (33), note the following relationship holds

$$\frac{1}{n^{IFTD}} \sum_i \sum_f \sum_d \sum_t (\psi_{ift} - \bar{\psi}_{IFT_{dD}}) (\bar{e}_{D_{ift}} - \bar{e}_{IFT_D}) = 0 \quad (34)$$

Since $\bar{e}_{D_{ift}} - \bar{e}_{IFT_D}$ is not destination specific, (34) can be rewritten as

$$\begin{aligned} & \frac{1}{n^{IFTD}} \sum_i \sum_f \sum_t \left[\sum_{d \in D_{ift}} (\psi_{ift} - \bar{\psi}_{IFT_{dD}}) (\bar{e}_{D_{ift}} - \bar{e}_{IFT_D}) \right] \\ &= \frac{1}{n^{IFTD}} \sum_i \sum_f \sum_t (\bar{e}_{D_{ift}} - \bar{e}_{IFT_D}) \sum_{d \in D_{ift}} (\psi_{ift} - \bar{\psi}_{IFT_{dD}}) \\ &= -\frac{1}{n^{IFTD}} \sum_i \sum_f \sum_t (\bar{e}_{D_{ift}} - \bar{e}_{IFT_D}) \sum_{d \in D_{ift}} \bar{\psi}_{IFT_{dD}} \\ &= 0 \end{aligned}$$

where the second and third equalities are based on the following property, i.e., as a deviation term, ψ_{ift} must satisfy

$$\sum_{d \in D_{ift}} \psi_{ift} = 0 \quad \forall ift \quad (35)$$

With (34), expression (33) can be simplified as

$$\frac{1}{n^{IFDT}} \sum_i \sum_f \sum_d \sum_t (\psi_{ifdt} - \bar{\psi}_{IFT_{dD}})(e_{dt} - \bar{e}_{IFT_{dD}}) = 0 \quad (36)$$

As shown in (36), in an unbalanced panel, our estimator requires a similar condition as (26).

B.2.3 Alternative partitions require a more demanding condition to mitigate potential endogenous selection of markets

We derive the condition for unbiasedness for two alternative and closely-related partition methods that are commonly used in the exchange rate pass through literature. We show these methods can produce biased estimates due to endogenous selection of markets even in the case where the marginal cost component is not destination-specific. In general, the condition of alternative partitions can be simplified into two terms, the covariance between the compositional error and exchange rates as in equation (36) and an additional term capturing the endogenous selection of markets. We start with an alternative partition of firm-product-destination and time fixed effects (ifd, t). Let T_{ifd} be the set of time periods a product-firm-destination triplet exports. The number of trading periods in this set is defined as $n_{ifd}^T \equiv |T_{ifd}|$. The unbiasedness condition can be decomposed into two terms using (4), i.e.,

$$\begin{aligned} & \frac{1}{n^{IFDT}} \sum_i \sum_f \sum_d \sum_t (\tilde{\psi}_{ifdt, T_{ifd}} - \frac{1}{n_{ifd}^T} \sum_{ifd \in IFD_{tT}} \tilde{\psi}_{ifdt, T_{ifd}})(\tilde{e}_{dt, T_{ifd}} - \frac{1}{n_{ifd}^T} \sum_{ifd \in IFD_{tT}} \tilde{e}_{dt, T_{ifd}}) + \\ & \frac{1}{n^{IFDT}} \sum_i \sum_f \sum_d \sum_t (\widetilde{\overline{m}c}_{ifdt, T_{ifd}} - \frac{1}{n_{ifd}^T} \sum_{ifd \in IFD_{tT}} \widetilde{\overline{m}c}_{ifdt, T_{ifd}})(\tilde{e}_{dt, T_{ifd}} - \frac{1}{n_{ifd}^T} \sum_{ifd \in IFD_{tT}} \tilde{e}_{dt, T_{ifd}}) = 0 \end{aligned} \quad (37)$$

where

$$\begin{aligned} \tilde{\psi}_{ifdt, T_{ifd}} &\equiv \psi_{ifdt} - \frac{1}{n_{ifd}^T} \sum_{t \in T_{ifd}} \psi_{ifdt} \\ \widetilde{\overline{m}c}_{ifdt, T_{ifd}} &\equiv \overline{m}c_{ifdt} - \frac{1}{n_{ifd}^T} \sum_{t \in T_{ifd}} \overline{m}c_{ifdt} \\ \tilde{e}_{dt, T_{ifd}} &\equiv e_{dt} - \frac{1}{n_{ifd}^T} \sum_{t \in T_{ifd}} e_{dt} \end{aligned}$$

Note that, even if the compositional term ψ_{ifdt} is always zero, the second line of expression (37) may not necessarily be zero due to endogenous selection. The time demeaning operation at the firm-product-time level changes the dimensions along which the unobserved marginal cost $\overline{m}c_{ifdt}$

varies, making $\widetilde{\overline{m}c}_{ift,T_{ifd}}$ a destination-specific object that moves along all four dimensions.

We now simplify equation (37) to get a clearer expression. Note that

$$\begin{aligned} \frac{1}{n_{tT}^{IFD}} \sum_{ifd \in IFD_{tT}} \widetilde{\overline{m}c}_{ift,T_{ifd}} &= \frac{1}{n_{tT}^{IFD}} \sum_{ifd \in IFD_{tT}} \overline{m}c_{ift} - \frac{1}{n_{tT}^{IFD}} \sum_{ifd \in IFD_{tT}} \frac{1}{n_{ifd}^T} \sum_{t \in T_{ifd}} \overline{m}c_{ift} \\ &= \overline{m}c_{IFD_{tT}} - \overline{m}c_{IFD_T} \\ \frac{1}{n_{tT}^{IFD}} \sum_{ifd \in IFD_{tT}} \widetilde{e}_{dt,T_{ifd}} &= \frac{1}{n_{tT}^{IFD}} \sum_{ifd \in IFD_{tT}} e_{dt} - \frac{1}{n_{tT}^{IFD}} \sum_{ifd \in IFD_{tT}} \frac{1}{n_{ifd}^T} \sum_{t \in T_{ifd}} e_{dt} \\ &= \overline{e}_{IFD_{tT}} - \overline{e}_{IFD_T} \end{aligned}$$

Thus, the second line of expression (37) can be rewritten as

$$\begin{aligned} &\frac{1}{n^{IFDT}} \sum_i \sum_f \sum_d \sum_t (\overline{m}c_{ift} - \overline{m}c_{T_{ifd}} - \overline{m}c_{IFD_{tT}} + \overline{m}c_{IFD_T}) (e_{dt} - \overline{e}_{T_{ifd}} - \overline{e}_{IFD_{tT}} + \overline{e}_{IFD_T}) \quad (38) \\ &= \frac{1}{n^{IFDT}} \sum_i \sum_f \sum_d \sum_t (\overline{m}c_{ift} - \overline{m}c_{T_{ifd}} - \overline{m}c_{IFD_{tT}} + \overline{m}c_{IFD_T}) e_{dt} \end{aligned}$$

Rearrange and get

$$\frac{1}{n^{DT}} \sum_d \sum_t e_{dt} \left[\frac{1}{n_{dt}^{IF}} \sum_{if \in IF_{dt}} (\overline{m}c_{ift} - \overline{m}c_{T_{ifd}} - \overline{m}c_{IFD_{tT}} + \overline{m}c_{IFD_T}) \right] \quad (39)$$

If the unbalanced panel arises from endogenous selection related to marginal cost shocks and exchange rate movements, expression (39) will in general not equal zero.

Therefore, the (ifd, t) fixed effects require the following condition to hold:

$$\begin{aligned} &\frac{1}{n^{IFDT}} \sum_i \sum_f \sum_d \sum_t (\psi_{ifdt} - \overline{\psi}_{T_{ifd}}) (e_{dt} - \overline{e}_{T_{ifd}} - \overline{e}_{IFD_{tT}} + \overline{e}_{IFD_T}) + \\ &\frac{1}{n^{DT}} \sum_d \sum_t e_{dt} \left[\frac{1}{n_{dt}^{IF}} \sum_{if \in IF_{dt}} (\overline{m}c_{ift} - \overline{m}c_{T_{ifd}} - \overline{m}c_{IFD_{tT}} + \overline{m}c_{IFD_T}) \right] = 0 \quad (40) \end{aligned}$$

As shown in (40), the (ifd, t) partition could suffer from the selection bias even if the marginal cost component is not destination specific, i.e., $\psi_{ifdt} = 0 \quad \forall ifdt$.

Taking S-period time differences makes the unobserved marginal cost uncontrollable: The condition for the procedure of taking time differences conditional on firm-product-

destination triplets and then adding time fixed effects can be written as

$$\begin{aligned} & \frac{1}{n^{IFDT}} \sum_i \sum_f \sum_d \sum_t (\Delta_{s|ifd} \psi_{ifdt} - \frac{1}{n_t^{IFD}} \sum_{ifd \in IFD_t} \Delta_{s|ifd} \psi_{ifdt}) (\Delta_{s|ifd} e_{dt} - \frac{1}{n_t^{IFD}} \sum_{ifd \in IFD_t} \Delta_{s|ifd} e_{dt}) + \\ & \frac{1}{n^{IFDT}} \sum_i \sum_f \sum_d \sum_t (\Delta_{s|ifd} \overline{mc}_{ifdt} - \frac{1}{n_t^{IFD}} \sum_{ifd \in IFD_t} \Delta_{s|ifd} \overline{mc}_{ifdt}) (\Delta_{s|ifd} e_{dt} - \frac{1}{n_t^{IFD}} \sum_{ifd \in IFD_t} \Delta_{s|ifd} e_{dt}) = 0 \end{aligned} \quad (41)$$

where

$$\begin{aligned} \Delta_{s|ifd} \psi_{ifdt} &\equiv \psi_{ifdt} - \psi_{ifd,t-s|ifd} \\ \Delta_{s|ifd} \overline{mc}_{ifdt} &\equiv \overline{mc}_{ifdt} - \overline{mc}_{if,t-s|ifd} \\ \Delta_{s|ifd} e_{dt} &\equiv e_{dt} - e_{d,t-s|ifd} \end{aligned}$$

Even if marginal cost is not destination-specific and the first line is always zero, estimates can still be biased as the second line of (41) can be very different from zero due to endogenous selection of markets. We find that further decomposing (41) does not provide more intuition. We turn to illustrating the properties of our estimator and comparing it to alternative methods with simulated examples.

B.3 Endogenous Market Selection and Destination Specific Marginal Costs: Simulations

B.3.1 Bias in endogenously unbalanced panels: a simulated example

We now inspect the analytics of estimation bias using a numerical example. To simplify the exposition, we suppress the product dimension. We write the optimal price of firm f in destination d denominated in the exporter's currency, p_{fdt} , as a function of the bilateral exchange rate, e_{dt} , the unobserved marginal cost, mc_{ft} , and a residual term, u_{fdt} . We define data generating processes for each of the terms in the price equation, e_{dt} , mc_{ft} and u_{fdt} :

$$p_{fdt} = \beta_1 e_{dt} + \beta_2 mc_{ft} + u_{fdt} \quad (42)$$

$$e_{dt} = \mathcal{F}_d + \mathcal{F}_t + \mathcal{F}_d * \mathcal{F}_t$$

$$mc_{ft} = \mathcal{C}_f + \mathcal{C}_t + \mathcal{C}_f * \mathcal{C}_t$$

$$u_{fdt} = \mathcal{I}_1 \mathcal{C}_f + \mathcal{I}_2 \mathcal{F}_d + \mathcal{I}_3 \mathcal{F}_t + \epsilon_{fdt} \quad (43)$$

where each of the factors in the data generating processes for e_{dt} , mc_{ft} and u_{fdt} are drawn from $N(0, 1)$ distributions:

$$\mathcal{F}_d \sim N(0, 1) \quad \mathcal{C}_f \sim N(0, 1) \quad \mathcal{F}_t = \mathcal{C}_t \sim N(0, 1) \quad \epsilon_{fdt} \sim N(0, 1) \quad (44)$$

and where the \mathcal{I}_j 's in (43) are indicator variables that take on values of 0 or 1.

In this example, the bilateral exchange rate, e_{dt} , co-moves with firm specific marginal costs, mc_{ft} , because of the assumption of perfect co-movement between the time-varying factors \mathcal{F}_t and \mathcal{C}_t . To capture possible practical difficulties of the estimation problem, we further allow for other unobserved confounding factors that are correlated with the bilateral exchange rate or the marginal cost to affect the optimal price. For example, $\mathcal{I}_2 = 1$ allows unobserved destination-specific factors \mathcal{F}_d to shift the price p_{fdt} beyond shifts caused by movements in bilateral exchange rates, e_{dt} , and marginal costs, mc_{ft} and helps to mitigate the problem in comparing nominal series across destinations.⁵⁰ Since \mathcal{F}_d is unobserved and is correlated with the bilateral exchange rate, allowing for a destination-specific factor creates an additional hurdle in identifying the parameter of interest β_1 .⁵¹

We simulate panels of price data under two different sets of assumptions about the data generating process for the residual term. First, we assume that the process is simple; the firm, destination, and time factors in the residual term are shut down (i.e., $\mathcal{I}_1 = \mathcal{I}_2 = \mathcal{I}_3 = 0$). Second, we assume a more complex data generating process for the residual term in which the firm, destination, and time factors are turned on (i.e., $\mathcal{I}_1 = \mathcal{I}_2 = \mathcal{I}_3 = 1$). For every simulation, we draw a balanced panel with 200 firms, 10 destinations and 10 time periods is generated, i.e., $n^F = 200, n^D = 10, n^T = 10$.

For every simulated balanced panel of price data, we generate a corresponding unbalanced panel in which the pattern of missing observations is systematically related to the size of the exchange rate and marginal cost shocks. We selectively drop observations from the simulated balanced panel according to the realised values of the exchange rate and marginal cost shocks as follows:

$$p_{fdt} = \begin{cases} \text{missing} & \text{if } \begin{array}{l} \text{the exchange rate shock } (e_{dt} - e_{dt-1}) \text{ is in the bottom 20\% at } t \\ \& \text{ the marginal cost shock } (mc_{ft} - mc_{ft-1}) \text{ is in the top 20\% at } t \end{array} \\ \text{observed} & \text{otherwise} \end{cases}$$

⁵⁰In our example, we allow difference in prices (denominated in the exporter's currency) across destinations to vary with bilateral exchange rates. In practice, however, nominal series (not only bilateral exchange rates, but also CPI) cannot be directly compared across destinations. Adding the shifter, $\mathcal{I}_2 = 1$, mitigates this problem. To see this, note the nominal exchange rate can be treated as the sum of the compatible bilateral exchange rate and an unobserved destination-specific shift, i.e., $e_{dt}^{nominal} = e_{dt}^{compatible} + \mu_d$.

⁵¹In the simulations of subsections B.3.1 and B.3.2, trade pattern fixed effects, $TP_{d,D_{ft}}$, rather than firm-trade pattern fixed effects, $TP_{fd,D_{ft}}$, are applied in the third step of TPSFE estimator. This is because the unobserved destination-specific shifter does not vary across firms under these simulation specifications. We discuss the difference between $TP_{d,D_{ft}}$ and $TP_{fd,D_{ft}}$ fixed effects in subsection B.3.3.

This selection rule filters out trade flows from exporters that receive a high negative exchange rate shock and a high positive marginal cost shock at time t . Note that a decrease in bilateral exchange rates means a depreciation of the destination currency. We set the markup elasticity to exchange rates, β_1 , to 1. This means that the exporter maintains a stable price in the destination currency when there is no change in its marginal cost. A depreciation in the destination currency reduces a firm’s profitability as it lowers the price received in the exporter’s currency. With $\beta_2 > 0$, a higher marginal cost induces a higher price and thus lowers the demand for the firm’s product. Therefore, both shocks put a negative pressure on a firm’s profitability. As a result, the exporter suffer the most from these two shocks may no longer find it optimal to trade.⁵²

Table 12 presents our results from running different estimators on the simulated datasets. The first column indicates the sources of variation that are active in the data generating process of u_{fdt} . In the first row, we set all indicator variables to zero. In the second row, we allow for the more complex data generating process for the residual, allowing the unobserved factors, $\mathcal{C}_f, \mathcal{F}_d, \mathcal{F}_t$, to shift the price p_{fdt} beyond the adjustments due to exchange rate, e_{dt} , and marginal cost mc_{ft} movements. The final column, “Calibrated Value of β_1 ,” reports the value of the underlying parameter, β_1 used to simulate the price data.

To start, note that, as long as the panel is balanced, all the estimators in table 12 return the correct estimate of the true parameter under both data generating processes for the residual (where the simple process is represented in the first row with (0 0 0) and the complex process is represented in the second row with (1 1 1)). In contrast, if the panel is unbalanced, only the TPSFE procedure is capable of producing the correct estimate. Taking S-period differences with time fixed effects (i.e., the S-Diff + (t) column) generates a significant upward bias, while high dimensional fixed effects partitioned as (fd, t) generate a significant downward bias. Our simulation suggests that one needs to be careful in applying multiple fixed effects in an unbalanced panel with endogenous trade patterns.

⁵²We also allow for other patterns of random drops to make sure the environment we constructed is similar to what we observe in the customs database. In particular, for each firm-year combination, we randomly generate 3 missing values (out of 10) along the destination dimension. We repeat this process for firm-destination combinations, and generate 3 missing values among the remaining observations. The advantage of using two separate processes compared to a random drop at the firm level lies in that the former allows the structure of missing values to differ along the time and destination dimensions.

Table 12: Performance of Estimators: Balanced v.s. Unbalanced Panel

			Balanced Panel			Unbalanced Panel			Calibrated
\mathcal{I}_1	\mathcal{I}_2	\mathcal{I}_3	S-Diff + (t)	HDFE (fd, t)	TPSFE	S-Diff + (t)	HDFE (fd, t)	TPSFE	Value of β_1
0	0	0	1.00*** (0.02)	1.00*** (0.02)	1.00*** (0.02)	1.36*** (0.03)	1.13*** (0.03)	1.00*** (0.03)	1.00
1	1	1	1.00*** (0.02)	1.00*** (0.02)	1.00*** (0.02)	1.65*** (0.03)	1.13*** (0.03)	1.00*** (0.03)	1.00

Note: Estimates and standard errors are calculated from the average of 200 simulations. Each simulation contains a randomly generated sample of 200 firms, 10 destinations and 10 time periods based on the data generating process specified in the paper. The ‘‘S-Diff + (t)’’ column represents estimates using S-period differenced variables at the firm-destination level adding time fixed effects. The ‘‘HDFE (fd, t)’’ column represents estimates applying firm-product and time fixed effects using the rehdf estimator. The ‘‘TPSFE’’ column represents estimates applying our trade pattern sequential fixed effects estimator.

We provide an analytical decomposition to show why the difference across estimates arises. We first evaluate the time differencing approach. After taking the S-period time difference, we obtain:

$$\Delta_{s|fd} p_{fdt} = \beta_1 \Delta_{s|fd} e_{dt} + \beta_2 \Delta_{s|fd} mc_{ft} + \Delta_{s|fd} u_{fdt} \quad (45)$$

where

$$\begin{aligned} \Delta_{s|fd} e_{dt} &= \mathcal{F}_t - \mathcal{F}_{t-s|fd} + \mathcal{F}_d (\mathcal{F}_t - \mathcal{F}_{t-s|fd}) \\ \Delta_{s|fd} mc_{ft} &= \mathcal{C}_t - \mathcal{C}_{t-s|fd} + \mathcal{C}_f (\mathcal{C}_t - \mathcal{C}_{t-s|fd}) \end{aligned}$$

From the expression $\Delta_{s|fd} mc_{ft}$, it can be seen that after S-differencing, the marginal cost term still varies at three dimensions, $f, d, \&t$. This variation over three dimensions makes the unobserved marginal cost term uncontrollable. Even the addition of multi-dimensional fixed effects will not be able to control for the unobserved marginal cost after S-differencing.

The specific advantage of our method is that it deals with the unobserved marginal cost in the first stage. As illustrated in equation (46), the destination demeaning process removes the unobserved marginal cost term so that it does not appear in the estimating equation. In this way, we effectively control for unobserved marginal cost.

$$\begin{aligned} \tilde{p}_{fdt, D_{ft}} &= \beta_1 \tilde{e}_{dt, D_{ft}} + \tilde{u}_{fdt, D_{ft}} \\ \tilde{e}_{dt, D_{ft}} &= e_{dt} - \frac{1}{n_{ft}^D} \sum_{d \in D_{ft}} e_{dt} = \tilde{\mathcal{F}}_{d, D_{ft}} (1 + \mathcal{F}_t) \end{aligned} \quad (46)$$

B.3.2 Simulated examples: various cases of destination-specific cost components

In what follows, we expand on our numerical example from section B.3.1 and discuss how composition error would affect our estimates under various scenarios. Specifically, we now allow for destination-specific composition changes or destination-specific marginal cost by specifying a term to capture deviations across destinations from the firm's mean marginal cost, ψ_{fdt} . In this analysis, we posit that the (destination-specific) composition term can be decomposed as follows:

$$\psi_{fdt} = \mathcal{A}_d * \mathcal{B}_{ft} \quad (47)$$

where the first term, \mathcal{A}_d is a factor that varies across destinations, and the second term, \mathcal{B}_{ft} captures time-varying factors within the firm. The key idea in our analysis is that the composition term, which is a deviation from a mean, ψ_{fdt} , must always sum to zero, $\frac{1}{n^D} \sum_d \psi_{fdt} = 0 \quad \forall ft$ as in (25). Analogously, the first term in (47) satisfies the restriction that destination deviations sum to zero, $\frac{1}{n^D} \sum_{d \in D_{ft}} \mathcal{A}_d = 0 \quad \forall ft$. This requirement rules out any general linear decomposition in the form:

$$\psi_{fdt} = \mathcal{A}_d + \mathcal{B}_{ft} + \mathcal{A}_d * \mathcal{B}_{ft}. \quad (48)$$

In equation (48), even if $\mathcal{A}_d = 0$ for all d , any non-zero realisation of \mathcal{B}_{ft} would imply that $\frac{1}{n^D} \sum_{d \in D_{ft}} \psi_{fdt}$ is also non-zero. Therefore, condition (25) would be violated.⁵³ For ψ_{fdt} to be firm-destination specific and condition (25) to be satisfied, ψ_{fdt} needs to have a functional form with a multiplicative relationship between the factors varying at the destination dimension, \mathcal{A}_d , and the factors varying at the firm-time dimensions, \mathcal{B}_{ft} , as specified in (47).

In what follows, we experiment with various formulations of \mathcal{A}_d and \mathcal{B}_{ft} , and compare the performance of estimators under these various formulations. We start with the case where components within the composition term, \mathcal{A}_d and \mathcal{B}_{ft} , are random and uncorrelated with factors in the exchange rate and the marginal cost, e_{dt} and mc_{ft} . The parameters in the price equation, β_1 and β_2 are set to 1 when simulating the data.

$$\begin{aligned} p_{fdt} &= \beta_1 e_{dt} + \beta_2 mc_{ft} + \psi_{fdt} + u_{fdt} \\ e_{dt} &= \mathcal{F}_d + \mathcal{F}_t + \mathcal{F}_d * \mathcal{F}_t \\ mc_{ft} &= \mathcal{C}_f + \mathcal{C}_t + \mathcal{C}_f * \mathcal{C}_t \\ \psi_{fdt} &= \mathcal{A}_d * \mathcal{B}_{ft} \\ \mathcal{A}_d &\sim N(0, 1) \quad \mathcal{B}_{ft} \sim N(\mu, \sigma) \end{aligned}$$

⁵³ However, restricting \mathcal{B}_{ft} to be zero is not an option as it makes the cost component destination specific (rather than firm-destination-specific) and brings us back to a case similar to the one discussed in subsection B.3.1 with $\mathcal{I}_2 = 1$.

The specification of the error term in the pricing equation throughout all our experiments with a composition error is the same as that in section B.3.1.

$$u_{f dt} = \mathcal{I}_1 \mathcal{C}_f + \mathcal{I}_2 \mathcal{F}_d + \mathcal{I}_3 \mathcal{F}_t + \epsilon_{f dt}$$

$$\mathcal{F}_d \sim N(0, 1) \quad \mathcal{C}_f \sim N(0, 1) \quad \mathcal{F}_t = \mathcal{C}_t \sim N(0, 1) \quad \epsilon_{f dt} \sim N(0, 1) \quad (49)$$

Table 13 presents our simulation results. In general, the estimates in Table 13 demonstrate a consistent pattern with those in Table 12. Since the composition term, $\psi_{f dt}$, is completely random, it does not change the estimation results.

Table 13: Performance of Estimators in the Presence of *Random* Composition Errors

			Balanced Panel			Unbalanced Panel			Calibrated
\mathcal{I}_1	\mathcal{I}_2	\mathcal{I}_3	S-Diff + (t)	HDFE (f, d, t)	TPSFE	S-Diff + (t)	HDFE (f, d, t)	TPSFE	Value of β_1
$\mu = 0$									
0	0	0	1.00*** (0.02)	1.00*** (0.02)	1.00*** (0.01)	1.36*** (0.02)	1.13*** (0.03)	1.00*** (0.03)	1.00
1	1	1	1.00*** (0.02)	1.00*** (0.02)	1.00*** (0.01)	1.63*** (0.02)	1.13*** (0.02)	1.00*** (0.03)	1.00
$\mu = 0.1$									
0	0	0	1.00*** (0.02)	1.00*** (0.02)	1.00*** (0.01)	1.36*** (0.02)	1.13*** (0.02)	1.00*** (0.02)	1.00
1	1	1	1.00*** (0.02)	1.00*** (0.02)	1.00*** (0.01)	1.62*** (0.02)	1.13*** (0.03)	1.00*** (0.03)	1.00

Note: Estimates and standard errors are calculated from the average of 200 simulations. Each simulation contains a randomly generated sample of 200 firms, 10 destinations and 10 time periods based on the data generating process specified in the paper. The “S-Diff + (t)” column represents estimates using S-period differenced variables at the firm-destination level adding time fixed effects. The “HDFE (f, d, t)” column represents estimates applying firm-product and time fixed effects using the reghdfe estimator. The “TPSFE” column represents estimates applying our trade pattern sequential fixed effects estimator.

In the next example, for each firm-time observation, we set the composition error to be positively correlated with the bilateral exchange rate along the destination dimension ($\mathcal{A}_d = \mathcal{F}_d$). Simulation results are shown in table 14. The TPSFE estimator is unbiased while the S-Diff and high dimensional fixed effects estimators continue to display the same pattern of bias we saw in the previous tables.

$$\begin{aligned}
p_{fdt} &= \beta_1 e_{dt} + \beta_2 mc_{ft} + \psi_{fdt} + u_{fdt} \\
e_{dt} &= \mathcal{F}_d + \mathcal{F}_t + \mathcal{F}_d * \mathcal{F}_t \\
mc_{ft} &= \mathcal{C}_f + \mathcal{C}_t + \mathcal{C}_f * \mathcal{C}_t \\
\psi_{fdt} &= \mathcal{F}_d * \mathcal{B}_{ft} \\
\mathcal{F}_d &\sim N(0, 1) \quad \mathcal{B}_{ft} \sim N(\mu, \sigma)
\end{aligned}$$

Table 14: Performance of Estimators:
Dependence of the Composition Error on Destination Factors

			Balanced Panel			Unbalanced Panel			Calibrated
\mathcal{I}_1	\mathcal{I}_2	\mathcal{I}_3	S-Diff + (t)	HDFE (fd, t)	TPSFE	S-Diff + (t)	HDFE (fd, t)	TPSFE	Value of β_1
$\mu = 0$									
0	0	0	1.00*** (0.02)	1.00*** (0.02)	1.00*** (0.01)	1.37*** (0.02)	1.13*** (0.02)	1.00*** (0.02)	1.00
1	1	1	1.00*** (0.02)	1.00*** (0.02)	1.00*** (0.01)	1.66*** (0.02)	1.14*** (0.02)	1.00*** (0.02)	1.00
$\mu = 0.1$									
0	0	0	1.00*** (0.02)	1.00*** (0.02)	1.00*** (0.01)	1.34*** (0.02)	1.13*** (0.02)	1.00*** (0.02)	1.00
1	1	1	1.00*** (0.02)	1.00*** (0.02)	1.00*** (0.01)	1.62*** (0.02)	1.13*** (0.02)	1.00*** (0.02)	1.00

Note: Estimates and standard errors are calculated from the average of 200 simulations. Each simulation contains a randomly generated sample of 200 firms, 10 destinations and 10 time periods based on the data generating process specified in the paper. The “S-Diff + (t)” column represents estimates using S-period differenced variables at the firm-destination level adding time fixed effects. The “HDFE (fd, t)” column represents estimates applying firm-product and time fixed effects using the reghdfe estimator. The “TPSFE” column represents estimates applying our trade pattern sequential fixed effects estimator.

We now turn to a setup in which the destination component of the composition error, \mathcal{A}_d , is correlated with the destination component of bilateral exchange rates *and* the firm-time component of the composition error, \mathcal{B}_{ft} is correlated with unobserved firm-time factors. Among all our simulations, this will highlight some potential estimation problems. This is so because, in this case, the bias of the composition error depends on two parameters, the parameter μ_3 controlling the conditional covariance at the destination dimension, $cov_{d|ft}(\psi_{fdt}, e_{dt})$, and the parameter μ_2

controlling conditional covariance at the firm-time dimension, $cov_{ft|d}(\psi_{fdt}, mc_{ft})$.

$$\begin{aligned}
 p_{fdt} &= \beta_1 e_{dt} + \beta_2 mc_{ft} + \psi_{fdt} + u_{fdt} \\
 e_{dt} &= \mathcal{F}_d + \mathcal{F}_t + \mathcal{F}_d * \mathcal{F}_t \\
 mc_{ft} &= \mathcal{C}_f + \mathcal{C}_t + \mathcal{C}_f * \mathcal{C}_t \\
 \psi_{fdt} &= \mu_3 \mathcal{F}_d * (\mu_1 + \mu_2 mc_{ft}) \\
 \mathcal{F}_d &\sim N(0, 1)
 \end{aligned}$$

Table 15: Performance of Estimators:
Destination and Firm-Time Composition Errors

μ_1	μ_2	μ_3	Balanced Panel			Unbalanced Panel			Theoretical Value of elasticity
			S-Diff + (t)	HDFE (fd, t)	TPSFE	S-Diff + (t)	HDFE (fd, t)	TPSFE	
0	1	1	1.99*** (0.02)	1.99*** (0.02)	1.99*** (0.01)	2.38*** (0.02)	2.13*** (0.02)	1.87*** (0.02)	2.00
0.1	1	1	1.99*** (0.02)	1.99*** (0.02)	1.99*** (0.02)	2.39*** (0.02)	2.14*** (0.02)	1.86*** (0.03)	2.00
0.1	0.1	1	1.10*** (0.01)	1.10*** (0.01)	1.10*** (0.01)	1.67*** (0.02)	1.23*** (0.02)	1.09*** (0.02)	1.10
0.1	1	0.1	1.10*** (0.01)	1.10*** (0.01)	1.10*** (0.01)	1.70*** (0.02)	1.23*** (0.02)	1.09*** (0.02)	1.10
0.1	0.1	0.1	1.01*** (0.01)	1.01*** (0.01)	1.01*** (0.01)	1.64*** (0.02)	1.14*** (0.02)	1.01*** (0.02)	1.01

Note: Estimates and standard errors are calculated from the average of 200 simulations. Each simulation contains a randomly generated sample of 200 firms, 10 destinations and 10 time periods based on the data generating process specified in the paper. The ‘‘S-Diff + (t)’’ column represents estimates using S-period differenced variables at the firm-destination level adding time fixed effects. The ‘‘HDFE (fd, t)’’ column represents estimates applying firm-product and time fixed effects using the reghdfe estimator. The ‘‘TPSFE’’ column represents estimates applying our trade pattern sequential fixed effects estimator.

Table 15 presents results on five parameterizations. The first row gives the results in the setup where both destination and firm-product covariances are high, i.e., $cov_{d|ft}(\psi_{fdt}, e_{dt}) = 1$ and $cov_{ft|d}(\psi_{fdt}, mc_{ft}) = 1$. In this setting, all three estimators generate estimates that are upward biased compared to the theoretical value of the elasticity.⁵⁴ Results in the second row show that changing the value of the mean of the component varying along the firm-time dimension, μ_1 , will not affect the estimate. As this is generally true in all specifications, in rows 3 through 5 we focus on variation in μ_2 and μ_3 . In Row 3, the destination dimension covariance is low but the firm-time dimension covariance is high. The case in row 4 is the reverse of the one in row 3. Row 5 presents the case where both covariances are low, $cov_{d|ft}(\psi_{fdt}, e_{dt}) = 0.1$ and $cov_{ft|d}(\psi_{fdt}, mc_{ft}) = 0.1$. The

⁵⁴The theoretical number in the table is calculated based on the statistical relationship imposed by a particular setup. In the case of Table 15, the theoretical number is calculated as $\beta_1 + \mu_3 * \mu_2$.

results in the last three rows of table 15 document that the composition term is a second order problem, i.e., the bias will be small if either of these two covariances is small.

We surmise that a large proportion of destination variation in nominal bilateral exchange rates is driven by nominal differences that can be considered randomly distributed. A high incidence of nominal noise in exchange rates would dilute the covariance term, resulting in a small $cov_{d|ft}(\psi_{f_{dt}}, e_{dt})$. Therefore, with a sufficiently small destination dimension covariance, $cov_{d|ft}(\psi_{f_{dt}}, e_{dt})$, and a reasonable firm-time level covariance, $cov_{ft|d}(\psi_{f_{dt}}, mc_{ft})$, the degree of composition bias should be small.

B.3.3 Simulated example: bias-variance trade-off in applying more disaggregated trade pattern fixed effects

Our proposed method can be implemented with trade pattern fixed effects or more disaggregated firm-product-trade pattern fixed effects. These two implementations are related to controlling for the confounding variables other than the unobserved marginal cost.

To see the difference in applying the trade pattern versus the firm-product-trade pattern fixed effects, consider two variants of example B.3.1, (50) and (51):

$$p_{f_{dt}} = \delta_f + \theta_d + mc_{ft} + e_{dt} + \epsilon_{f_{dt}} \quad (50)$$

$$p_{f_{dt}} = \delta_{fd} + mc_{ft} + e_{dt} + \epsilon_{f_{dt}} \quad (51)$$

where δ_f , θ_d and δ_{fd} represent the unobserved factors varying along different dimensions, and are potentially correlated with the unobserved marginal cost mc_{ft} and the observed bilateral exchange rates e_{dt} . Specification (51) differs from (50) in that it allows the unobserved factors δ_{fd} to be firm-destination specific, such as brand name, taste, and distribution cost. Note that, in both cases, the unobserved marginal cost is differenced out after taking destination demean (the first step of TPSFE), i.e.,

$$\tilde{p}_{f_{dt}, D_{ft}} = \tilde{\theta}_{d, D_{ft}} + \tilde{e}_{dt, D_{ft}} + \tilde{\epsilon}_{f_{dt}, D_{ft}} \quad (52)$$

$$\tilde{p}_{f_{dt}, D_{ft}} = \tilde{\delta}_{fd, D_{ft}} + \tilde{e}_{dt, D_{ft}} + \tilde{\epsilon}_{f_{dt}, D_{ft}} \quad (53)$$

Comparing (52) to (53), it can be seen that adding the trade pattern fixed effect is sufficient to control for the unobserved $\tilde{\theta}_{d, D_{ft}}$. However, firm-trade pattern fixed effects are needed to control for $\tilde{\delta}_{fd, D_{ft}}$ in (53).

Although adding more disaggregated trade pattern fixed effects seems to be a safer option, there is a cost associated with adding higher level fixed effects. There is a standard bias-variance trade-off as in most estimation problems. Table 16 shows the corresponding simulation results for

the data generating processes of (50) and (51), where

$$\begin{aligned}\theta_d &= \mathcal{F}_d \sim N(0, 1); & \delta_f &= \mathcal{C}_f \sim N(0, 1); & \delta_{fd} &= \mathcal{F}_d * \mathcal{C}_f; \\ \mathcal{C}_t &= \mathcal{F}_t \sim N(0, 1); & \epsilon_{fdt} &\sim N(0, 1); \\ e_{dt} &= \mathcal{F}_d + \mathcal{F}_t + \mathcal{F}_d * \mathcal{F}_t; & mc_{ft} &= \mathcal{C}_f + \mathcal{C}_t + \mathcal{C}_f * \mathcal{C}_t.\end{aligned}$$

As shown in Table 16, the standard error is much higher with $\tilde{\delta}_{fd, D_{ft}}$ in the column TPSFE (fdD) compared to $\tilde{\delta}_{d, D_{ft}}$ in column TPSFE (dD).

Table 16: Performance of Estimators:
Bias-Variance Trade-off in Applying More Disaggregated Trade Pattern Fixed Effects

(50) $f + d$	(51) fd	Balanced Panel			Unbalanced Panel			Calibrated Value of β_1
		HDFE (fd, t)	TPSFE (dD)	TPSFE (fdD)	HDFE (fd, t)	TPSFE (dD)	TPSFE (fdD)	
0	0	1.00*** (0.02)	1.00*** (0.01)	1.00*** (0.01)	1.13*** (0.02)	1.00*** (0.02)	1.00*** (0.27)	1.00
1	0	1.00*** (0.02)	1.00*** (0.01)	1.00*** (0.01)	1.13*** (0.02)	1.00*** (0.02)	0.95*** (0.30)	1.00
0	1	1.00*** (0.02)	1.00*** (0.02)	1.00*** (0.01)	1.13*** (0.02)	0.87*** (0.03)	0.96*** (0.28)	1.00

Note: Estimates and standard errors are calculated from the average of 200 simulations. Each simulation contains a randomly generated sample of 200 firms, 10 destinations and 10 time periods based on the data generating process specified in the paper. ‘HDFE (fd, t)’: estimates applying firm-product and time fixed effects with the reghdfe estimator; ‘TPSFE (dD)’: estimates applying TPSFE with trade pattern fixed effects; ‘TPSFE (fdD)’: estimates applying TPSFE with firm-trade pattern fixed effects.

Empirically, we find that the larger standard error associated with the firm-product-trade pattern fixed effects is not a problem when the estimator is applied to the customs data with millions of observations. Therefore, we use firm-product-trade pattern fixed effects as our benchmark specification.

B.4 Robustness Checks on Comparative Assessment of Estimators

Table 17: Comparison across Estimators (2006-2014)

	TPSFE (ifd,TP)	TPSFE (d,TP)	No Trade Pattern	HDFE (<i>ift, d</i>)	HDFE (<i>ifd, t</i>)	S-Diff + (<i>t</i>)	S-Diff + (<i>ifd, t</i>)	S-Diff + (<i>ift, d</i>)	n. of obs
Destination Demean	Yes	Yes	Yes	No	No	No	No	No	
S-period Difference	No	No	No	No	No	Yes	Yes	Yes	
Fixed Effects	Firm Product Trade Pattern ($TP_{ifd, D_{ift}}$)	Trade Pattern ($TP_{d, D_{ift}}$)	Destination (<i>d</i>)	(<i>ift, d</i>)	(<i>ifd, t</i>)	Time (<i>t</i>)	(<i>ifd, t</i>)	(<i>ift, d</i>)	
Stage 8									
All Products	0.106*** (0.006)	0.087*** (0.005)	0.021*** (0.000)	0.092*** (0.007)	0.138*** (0.009)	0.219*** (0.008)	0.268*** (0.018)	0.155*** (0.011)	4,863,196
High Differentiation	0.196*** (0.010)	0.146*** (0.009)	0.015*** (0.000)	0.160*** (0.012)	0.241*** (0.015)	0.363*** (0.013)	0.557*** (0.029)	0.274*** (0.018)	1,951,051
Low Differentiation	0.064*** (0.007)	0.058*** (0.007)	0.024*** (0.000)	0.054*** (0.008)	0.085*** (0.011)	0.136*** (0.010)	0.119*** (0.023)	0.095*** (0.013)	2,912,145
Stage 7									
All Products	0.106*** (0.006)	0.073*** (0.004)	0.021*** (0.000)	0.080*** (0.003)	0.109*** (0.003)	0.166*** (0.003)	0.135*** (0.005)	0.110*** (0.004)	19,450,040
High Differentiation	0.196*** (0.010)	0.120*** (0.008)	0.014*** (0.000)	0.112*** (0.005)	0.160*** (0.005)	0.233*** (0.005)	0.246*** (0.008)	0.148*** (0.006)	8,322,706
Low Differentiation	0.064*** (0.007)	0.049*** (0.006)	0.026*** (0.000)	0.056*** (0.003)	0.073*** (0.004)	0.118*** (0.004)	0.057*** (0.007)	0.081*** (0.005)	11,127,334

Note: Each cell reports the estimated markup elasticity to exchange rates from the estimation method specified on top of each column. Destination CPI, real GDP and M/GDP controls are included in all estimation methods; related estimates are omitted for conciseness. Each row indicates a different subsample. Within in a row, all methods are applied based on the same sample. The number of observations in the last column corresponds to Stages 7 and 8 of the data cleaning procedure specified in appendix C.4. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *.

B.5 Relation to De Loecker, Goldberg, Khandelwal and Pavcnik (2016)

In this subsection, we extend the framework of De Loecker, Goldberg, Khandelwal and Pavcnik (2016) to add a destination dimension, and discuss the structural assumptions that would be required for our main identification condition (5) to be satisfied in this framework.

B.5.1 Structural Interpretation of Assumptions Required by Our Estimator

We start writing the production function as follows.

$$Q_{fidt} = F_{fi}(\mathbf{V}_{fidt}, \mathbf{K}_{fidt})\Omega_{fit}\Psi_{fid} \quad (54)$$

where Q_{fidt} represents the quantity of exports for product i from firm f to destinations d at time t ; \mathbf{V}_{fidt} denotes a vector of variable inputs, $\{V_{fidt}^1, V_{fidt}^2, \dots, V_{fidt}^v\}$; \mathbf{K}_{fidt} denotes a vector of dynamic inputs; a firm-product pair make decisions on allocating its dynamic inputs across destinations D_{fit} in each time period, $\{K_{fidt}^1, K_{fidt}^2, \dots, K_{fidt}^k\}$. We stress that the above function allows for destination-specific inputs $\{\mathbf{V}_{fidt}, \mathbf{K}_{fidt}\}$ as well as destination-specific productivity differences, Ψ_{fid} , at the firm and product level. In addition, we allow for the production function and Hicks-neutral productivity to be firm-product specific.

Specifically, we posit the following:

1. The production technology is firm-product-specific.
2. $F_{fi}(\cdot)$ is continuous and twice differentiable w.r.t. at least one element of V_{fidt} , and this element of V_{fidt} is a static (i.e., freely adjustable or variable) input in the production of product i .
3. $F_{fi}(\cdot)$ is constant return to scale.
4. Hicks-neutral productivity Ω_{fit} is log-additive.
5. The destination specific technology advantage Ψ_{fid} takes a log-additive form and is not time varying.
6. Input prices \mathbf{W}_{fit} are firm-product-time specific.
7. The state variables of the firm are

$$\mathbf{s}_{fit} = \{D_{fit}, \mathbf{K}_{fit}, \Omega_{fit}, \Psi_{fid}, \mathbf{G}_{fi}, \mathbf{r}_{fidt}\} \quad (55)$$

where \mathbf{G}_{fi} includes variables indicating firm and product properties, e.g., firm registration types, product differentiation indicators. \mathbf{r}_{fidt} collects other observables including variables

that track the destination market conditions, such as the bilateral exchange rate and destination CPI.

8. Firms minimize short-run costs taking output quantity, Q_{fidt} , and input prices, \mathbf{W}_{fit} , at time t as given.

The assumptions 1, 2, 4, 8 are standard in the literature. They are posited by De Loecker, Goldberg, Khandelwal and Pavcnik (2016) but in our version we allow the production function to be firm specific and the Hicks-neutral productivity to be product-specific. Compare to the conditions assumed in the literature, assumption 5 is a relaxation: it allows for the possibility that (additive) productivity be destination-specific.

Assumptions 6 and 7 allow prices of inputs to be firm and product specific. These two conditions indicate that firms source inputs at the product level, and then allocate these inputs into production for different destinations. Note that the firm can arrange different quantities of inputs and have different marginal costs across destinations for the same product.

The assumption that is crucial to our identification is that the production technology is constant returns to scale (condition 3). This condition implies that the marginal cost at the firm-product-destination level does not depend on the quantity produced. If changes in relative demand and exports across destinations were systematically associated to changes in relative marginal costs, condition 5 would be violated. As discussed in the next subsection, looking at the solution of the firms' cost minimization problem, condition 3 ensures that the difference in the marginal costs across destinations only reflects technology differences varying at the destination dimension, i.e., $\frac{\Psi_{fid'}}{\Psi_{fid}}$.

B.5.2 The cost minimization problem by firm-product pair

Write the cost function

$$\begin{aligned} \mathcal{L}(\mathbf{V}_{fidt}, \mathbf{K}_{fidt}, \lambda_{fidt}) = & \sum_{v=1}^V W_{fit}^v \sum_{d \in D_{ift}} V_{fidt}^v + \sum_{k=1}^K R_{fit}^k \left(\sum_{d \in D_{fit}} K_{fidt}^k - K_{fit}^k \right) \\ & + \sum_{d \in D_{fit}} \lambda_{fidt} [Q_{fidt} - F_{fi}(\mathbf{V}_{fidt}, \mathbf{K}_{fidt}) \Omega_{fit} \Psi_{fid}] \end{aligned}$$

where K_{fit}^k is the accumulated capital input k in the previous period; K_{fidt}^k stands for the corresponding allocation for destination d ; R_{fit}^k is the implied cost of capital.⁵⁵

The F.O.C.s of the cost minimization problem are

⁵⁵The assumption that the production function $F_{fi}(\cdot)$ is firm-product-specific ensures the implied cost of capital R_{fit}^k being not destination-specific.

$$\frac{\partial \mathcal{L}_{fit}}{\partial V_{fidt}^v} = W_{fit}^v - \lambda_{fidt} \Omega_{fit} \Psi_{fid} \frac{\partial F_{fi}(\cdot)}{\partial V_{fidt}^v} = 0 \quad (56)$$

$$\frac{\partial \mathcal{L}_{fit}}{\partial K_{fidt}^k} = R_{fit}^k - \lambda_{fidt} \Omega_{fit} \Psi_{fid} \frac{\partial F_{fi}(\cdot)}{\partial K_{fidt}^k} = 0 \quad (57)$$

Conditions (56) and (57) need to hold across inputs and across destinations, which implies the following:

$$\frac{W_{fit}^1}{W_{fit}^v} = \frac{\frac{\partial F_{fi}(\cdot)}{\partial V_{f,i,1,t}^1}}{\frac{\partial F_{fi}(\cdot)}{\partial V_{f,i,1,t}^v}} = \frac{\frac{\partial F_{fi}(\cdot)}{\partial V_{f,i,2,t}^1}}{\frac{\partial F_{fi}(\cdot)}{\partial V_{f,i,2,t}^v}} = \dots = \frac{\frac{\partial F_{fi}(\cdot)}{\partial V_{f,i,D_{fit},t}^1}}{\frac{\partial F_{fi}(\cdot)}{\partial V_{f,i,D_{fit},t}^v}} \quad \forall v = 1, \dots, V \quad (58)$$

$$\frac{W_{fit}^v}{R_{fit}^k} = \frac{\frac{\partial F_{fi}(\cdot)}{\partial V_{f,i,1,t}^v}}{\frac{\partial F_{fi}(\cdot)}{\partial K_{f,i,1,t}^k}} = \frac{\frac{\partial F_{fi}(\cdot)}{\partial V_{f,i,2,t}^v}}{\frac{\partial F_{fi}(\cdot)}{\partial K_{f,i,2,t}^k}} = \dots = \frac{\frac{\partial F_{fi}(\cdot)}{\partial V_{f,i,D_{fit},t}^v}}{\frac{\partial F_{fi}(\cdot)}{\partial K_{f,i,D_{fit},t}^k}} \quad \forall v, k \quad (59)$$

Note that the production function is assumed to be firm-product specific and constant return to scale. Together with equations (58) and (59), these assumptions imply that the allocation of variable inputs is inversely proportional to the ratio of the productivity deflated outputs across destinations, that is,

$$\frac{Q_{fidt}}{\Omega_{fit} \Psi_{fid}} = c \cdot \frac{Q_{fid't}}{\Omega_{fit} \Psi_{fid'}} \quad \rightarrow \quad c \mathbf{V}_{fidt}^* = \mathbf{V}_{fid't}^* \quad \text{and} \quad c \mathbf{K}_{fidt}^* = \mathbf{K}_{fid't}^* \quad (60)$$

Utilizing the relationship of (60) and the assumption that $F_{fi}(\cdot)$ is constant return to scale, we can show

$$c_{fidt} \cdot \frac{\partial F_{fi}(\mathbf{V}_{fidt}^*, \mathbf{K}_{fidt}^*)}{\partial V_{fidt}^v} = \frac{\partial [c_{fidt} F_{fi}(\mathbf{V}_{fidt}^*, \mathbf{K}_{fidt}^*)]}{\partial V_{fidt}^v} = \frac{\partial F_{fi}(c_{fidt} \mathbf{V}_{fidt}^*, c_{fidt} \mathbf{K}_{fidt}^*)}{\partial V_{fidt}^v} = \frac{\partial F_{fi}(\mathbf{V}_{fid't}^*, \mathbf{K}_{fid't}^*)}{\partial V_{fid't}^v} \quad (61)$$

where $c_{fidt} \equiv \frac{Q_{fidt} \Psi_{fid'}}{Q_{fid't} \Psi_{fid}}$.

Rearranging (58) yields:

$$\lambda_{fidt} = \left(\frac{\Omega_{fit} \Psi_{fid} \frac{\partial F_{fi}(\mathbf{V}_{fidt}, \mathbf{K}_{fidt})}{\partial V_{fidt}^v}}{W_{fit}^v} \right)^{-1} \quad (62)$$

Under the above setup, the relative marginal cost across destinations is static, depending on the relative productivity difference across destinations, i.e.,

$$\frac{\lambda_{fidt}/Q_{ifdt}}{\lambda_{fid't}/Q_{ifd't}} = \frac{\Psi_{fid'}}{\Psi_{fid}} \quad (63)$$

Although the marginal cost is firm-product-destination specific and time varying, the relative marginal cost is not. Therefore, condition (5) is satisfied.

B.5.3 An alternative approach

An alternative approach to reconcile our work with De Loecker, Goldberg, Khandelwal and Pavcnik (2016) could consist of directly redefining what a product variety is in their model. Namely, if one redefines a product-destination pair as a variety, i.e., $j = \{i, d\}$, then the original setting and assumptions will go through without any change.

We argue that this approach is not very useful, for two reasons. The first one is practical. De Loecker, Goldberg, Khandelwal and Pavcnik (2016) define a product variety as a two-digit industry. The need to define a product at industry level is mainly due to data limitations. If one adopts a more refined product definition, for instance, the estimator by De Loecker, Goldberg, Khandelwal and Pavcnik (2016) would suffer from a small sample problem—there would not be enough power to estimate. The small sample problem will be much more severe if one defines a product-destination pair as a variety. This is due not only to the smaller number of observations in each cell, but also to the frequent changes in the set of destinations a firm exports a product to.

The second reason is related to conceptual assumptions regarding production functions. De Loecker, Goldberg, Khandelwal and Pavcnik (2016) relies on the assumption that the production function is the same for single- and multi-product firms. When redefining a product-destination pair as a variety, the identification condition would require the production function to be product-destination specific and invariant along the firm dimension. In the context of our problem, controlling for firm-product level marginal cost is the primary concern. We think that keeping the flexibility of the production function at the product level is extremely valuable.

C Data

C.1 Descriptive Statistics of Chinese Customs Data

Table 18 documents China’s dramatic increase in export value over the 2000-2014 period. The figures in the table emphasizes that the extent of the growth at the extensive margin, including both net entry of new firm, and net entry of firm-product.

Table 18: Chinese exports: firms, products and values, 2000-2014

	Products	Exporters	Product- Exporter Pairs	Obs.	Value (billions US\$)
2000	6,712	62,746	904,111	1,953,638	249
2001	6,722	68,487	991,015	2,197,705	291
2002	6,892	78,607	1,195,324	2,672,837	325
2003	7,013	95,683	1,475,588	3,328,320	438
2004	7,017	120,567	1,826,966	4,125,819	593
2005	7,125	142,413	2,277,801	5,252,820	753
2006	7,171	171,169	2,907,975	6,312,897	967
2007	7,172	193,567	3,296,238	7,519,615	1,220
2008	7,213	206,529	3,244,484	7,995,266	1,431
2009	7,322	216,219	3,363,610	8,263,509	1,202
2010	7,363	234,366	3,847,708	9,913,754	1,577
2011	7,404	254,617	4,153,534	10,645,699	1,898
2012	7,564	266,842	4,171,770	11,057,899	2,016
2013	7,579	279,428	4,140,897	11,643,683	2,176
2014	7,641	295,309	4,555,912	12,297,195	2,310

C.2 The “Happy Few:” Multi-product, multi-destination exporters

Using any cross section of the Chinese Customs Database, one can easily document that, also in the case of China, a “happy few” exporters are responsible for most of a country’s exports (see Mayer, Melitz and Ottaviano (2014)). The table 19 shows statistics for the year 2007. The top panel provides a breakdown of the number of export transactions by the count of products and destinations served by a firm exporting from China. The bottom panel presents the corresponding

Table 19: Multi-product, multi-destination exporters (2007)

No. of Products		Number of Countries				Total
		1	2-5	6-10	10+	
by Share of Exporters	1	13.5	6.4	1.6	1.2	22.6
	2-5	9.5	16.5	5.8	5.8	37.6
	6-10	2.2	5.5	3.3	4.4	15.3
	10+	2.1	4.7	4.1	13.6	24.6
	Total	27.2	33.1	14.7	25.0	100.0
by Share of Exports	1	1.2	1.3	0.8	1.3	4.7
	2-5	1.9	4.3	3.3	8.8	18.4
	6-10	0.6	2.2	2.0	8.1	13.0
	10+	1.6	4.0	4.2	54.0	63.9
	Total	5.4	11.9	10.4	72.3	100.0

Note: Each cell in the top panel is the percentage of observations in the Chinese customs data in 2007 that fall under the relevant description. The bottom panel presents the corresponding value of exports.

shares of export *value* by firms that differ by exported product count and foreign markets reached. Overall, we see that multi-destination exporters generate almost three-quarters of export transactions (row 5 of the top panel of table 19, 33.1+14.7+25.0) and are responsible for 94.6% of export value (row 5 of the bottom panel of table 19).⁵⁶ These statistics highlight two important facts: (1) the identification scheme based on multi-destination exporters uses observations from those firms that are most important to China’s trade and (2) the vast majority of firms are *not* single-product exporters. It is worth stressing that the shares of export transactions and export value by count of products and destination markets are relatively stable across years in our sample period. Tables for other years are available in an on-line appendix.

The total number of active exporters increased dramatically over our sample period, from 62,746 in 2000 to 295,310 in 2014. We track the total number of actively traded products by counting unique product-exporter pairs. We find that this measure increased roughly at the same pace as the number of exporters, from about 904 thousand in 2000 to 4.56 million in 2014. The value of total exports measured in dollars increased ten-fold, from 2000 to 2014. Additional details are provided in the on-line appendix.

⁵⁶Conversely, we see that transactions by single-destination firms account for a small share of total Chinese export value. In the top left cell of the top panel of table 19, we observe that 13.5% of observations on exports in the Chinese Customs Database were articles exported to a single destination by a single product firm. However, these transactions comprised only 1.2% of Chinese export value in 2007. The bottom row of the top panel shows that slightly more than one quarter of export transactions in 2007 were products exported by a firm to a single destination. However, the last row of the bottom panel indicates that the value of these transactions by single-destination exporters was only 5.4% of total Chinese exports.

C.3 In which currency do exporters from China invoice?

The Chinese Customs Authority reports the value of export shipments in US dollars, but does not provide any information about whether the trade was invoiced in US dollars, renminbi, another vehicle currency or the currency of the destination. We turn to the customs records of Her Majesty’s Revenue and Customs (HMRC) in the United Kingdom, one of China’s major destination markets, to shed light on this issue.

We interpret the widespread prevalence of dollar invoicing for a country that issues its own vehicle currency as suggestive that Chinese exports to other countries, including those that do not issue vehicle currencies, are likely predominately invoiced in US dollars.

Since 2010, HMRC has recorded the invoicing currency for the vast majority of import and export transactions between the UK and non-EU trading partners.⁵⁷

Figure 4 presents the shares of import transactions and import value into the UK from China by invoicing currency.⁵⁸ Results are reported for three currencies, the euro (EUR), pound sterling (GBP), and the US dollar (USD). All transactions that use other currencies of invoice, for example, the Swiss franc, Japanese yen or Chinese renminbi, are aggregated into the category “Other.”⁵⁹ In each graph, the dark bar refers to the share of transactions and the light grey bar refers to the share of import value reported in the relevant currency.

The first point to note is that virtually all of the UK’s imports from China are invoiced in one of three major currencies: the pound sterling (GBP), the US dollar (USD), or the euro (EUR). Very little trade is invoiced in any other currency, including the Chinese renminbi.

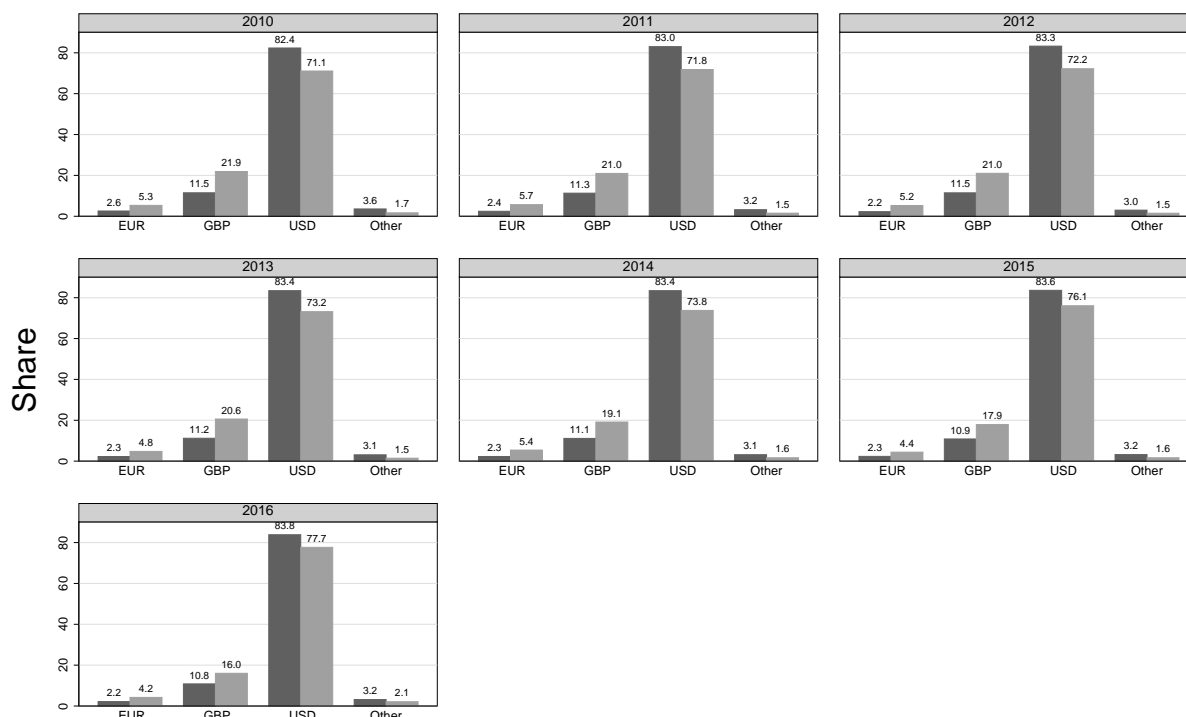
The second striking point is that the most important currency for Chinese exports to the UK is the US dollar. The dollar’s prominence as the invoicing currency of choice for Chinese exports to the UK rose over 2010-2016 with the share of import value growing from 71.1% to 77.7%. The share of transactions invoiced in US dollars was stable at around 83% throughout the 2010-2016

⁵⁷The reporting requirements for invoice currency are described in *UK Non-EU Trade by declared currency of Invoice (2016)*, published 25 April 2017. See page 7: “Only data received through the administrative Customs data collection has a currency of invoice declared... For Non-EU import trade, businesses must submit the invoice currency when providing customs declarations. However, 5.0 per cent of Non-EU import trade value [in 2016] did not have a currency... This was accounted for by trade reported through separate systems, such as parcel post and some mineral fuels. For Non-EU export trade, businesses are required to declare invoice currency for declarations with a value greater than £100,000. As a result of this threshold and trade collected separately (reasons outlined above) 10.1 per cent of Non-EU export trade [in 2016] was declared without a currency.”

⁵⁸ To construct this figure, we begin with the universe of UK import transactions for goods originating from China over 2010-2016. Then, we aggregate all transactions within a year that are reported for a firm-CN08product-quantity measure-currency quadruplet to an annual observation for that quadruplet. The variable “quantity measure” records whether a transaction for a CN08 product is reported in kilograms or a supplementary quantity unit like “items” or “pairs.” This leaves us with 2.004 million annual transactions which we use to construct figure 4.

⁵⁹ We do not report the number of transactions for which the currency is not reported; the number of transactions with no currency reported falls below HMRC Datalab’s threshold rule of firms in at least one year and is, for confidentiality reasons, omitted from the figure.

Figure 4: Invoicing currencies for UK imports from China



Black: Share of Transactions; Grey: Share of Trade Value
 Source: Calculations based on HMRC administrative datasets.

period.⁶⁰ Over this same period, the pound’s importance as an invoicing currency for imports from China fell. While the share of transactions invoiced in sterling held steady at 10-12% over the period, the share of import value fell from a high of 21.9% in 2010 to a low of 16.0% by 2016. The importance of the euro as an invoicing currency for Chinese exports to Britain was low throughout the 2010-2016 period.

In figure 5 we present information on the currency of invoicing for UK exports to China. Firms are only required to report the currency of invoicing for export transactions whose value exceeds £100,000. The share of export transactions and value for which no invoicing currency is reported is sizeable. In figure 5, these are indicated by “NR.”⁶¹

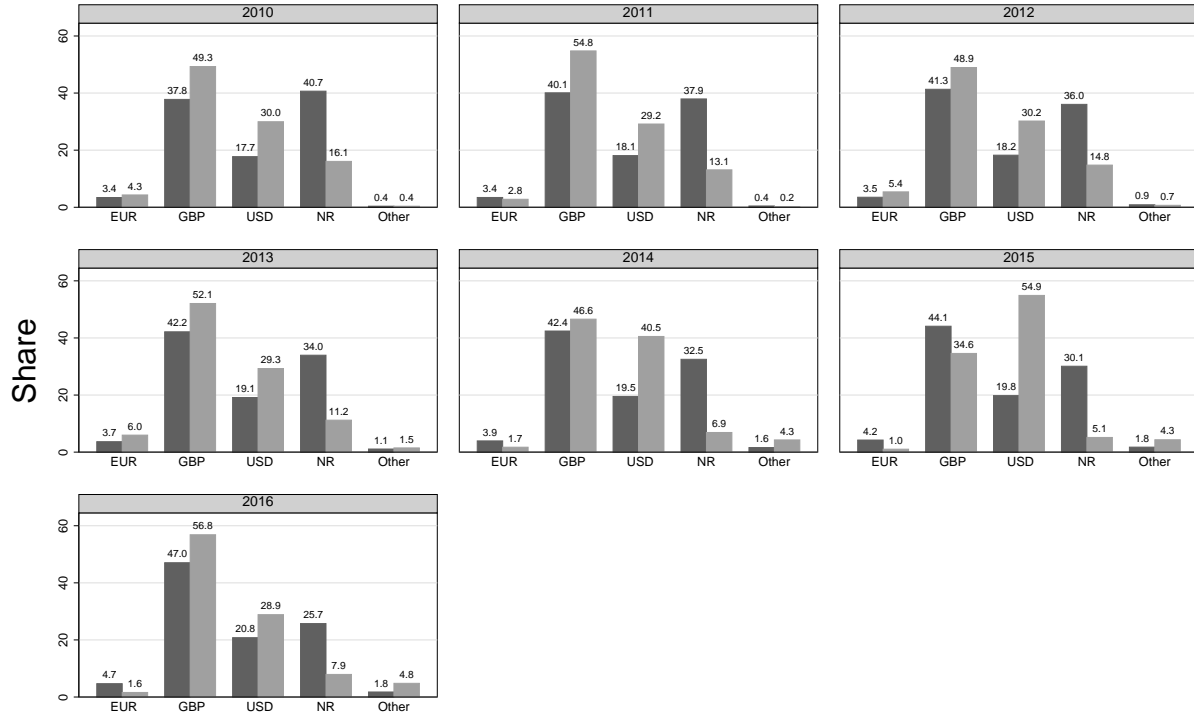
In almost all years the British pound sterling is the most important currency of invoicing for exports to China, both in transaction and value terms. Interestingly, the sterling does not dominate invoicing of exports entirely; substantial shares of exports are invoiced in US dollars. The euro appears to play a minor role and other currencies, including the Chinese renminbi, are rarely used.

The proportion of Britain’s exports for which no currency is reported declines over time. Pre-

⁶⁰See also Goldberg and Tille (2008) and Goldberg and Tille (2016) who document relatively large shares of exports invoiced in dollars for many countries.

⁶¹To construct figure 5 we follow the same procedure described above for imports. We arrive at approximately 266 thousand annual transactions which we use to construct the figure.

Figure 5: Invoicing currencies for UK exports to China



Black: Share of Transactions; Grey: Share of Trade Value
 Source: Calculations based on HMRC administrative datasets.

sumably this is related to an increase in the nominal value of trade transactions such that a greater proportion exceed the £100,000 reporting requirement over time.

This evidence is relevant to our empirical analysis to follow, insofar as a firm that invoices in a vehicle currency, say dollars, also prices its good in that currency. Suppose that the firm sets one single price for its product in dollars: this practice (arguably maximizing the markup relative to global demand) would rule out destination specific adjustment in markups. In this case, our TPSFE estimation should yield insignificant results. The same would be true if firms set different dollar prices across markets (in line with evidence of deviations from the law of one price), but do not adjust them in response to fluctuations in the exchange rate.

This suggests that our TPSFE estimator of markup elasticities can provide evidence on a relevant implication of what Gopinath has dubbed the ‘International Price System.’ Specifically, our empirical findings can inform us about the possibility of dollar invoicing translating into a ‘reference price system’ in which firms do not exploit market-specific demand elasticities, but price in relation to global demand. If a reference price system dominates, we would expect to observe firms setting one prevailing price in the global market for manufactured goods as they do for commodities.

C.4 Price Changes and Trade Pattern Dummies

In this subsection, we show how we build our (unbalanced) panel. We will rely on an example to explain how we identify price changes at the firm-product destination level and trade patterns across destinations at the firm-product level in the data.

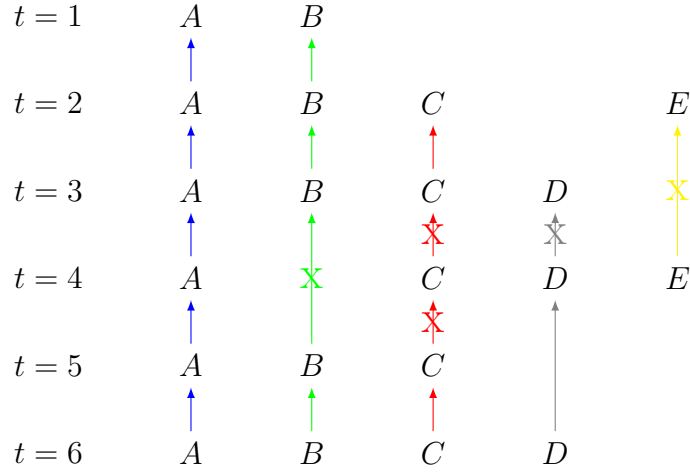
Consider a firm exporting a product to five countries, A through E, over 6 time periods. In the following matrix, $t = 1, 2, 3, \dots$ indicates the time period and A, B,C,D, E indicates the country. Empty elements in the matrix indicate that there was no trade.

$t = 1$	A	B			
$t = 2$	A	B	C		E
$t = 3$	A	B	C	D	
$t = 4$	A		C	D	E
$t = 5$	A	B	C		
$t = 6$	A	B	C	D	

The following matrix records export prices by destination country and time:

$$\begin{bmatrix} p_{A,1} & p_{B,1} & \cdot & \cdot & \cdot \\ p_{A,2} & p_{B,2} & p_{C,2} & \cdot & p_{E,2} \\ p_{A,3} & p_{B,3} & p_{C,3} & p_{D,3} & \cdot \\ p_{A,4} & \cdot & p_{C,4} & p_{D,4} & p_{E,4} \\ p_{A,5} & p_{B,5} & p_{C,5} & \cdot & \cdot \\ p_{A,6} & p_{B,6} & p_{C,6} & p_{D,6} & \cdot \end{bmatrix}$$

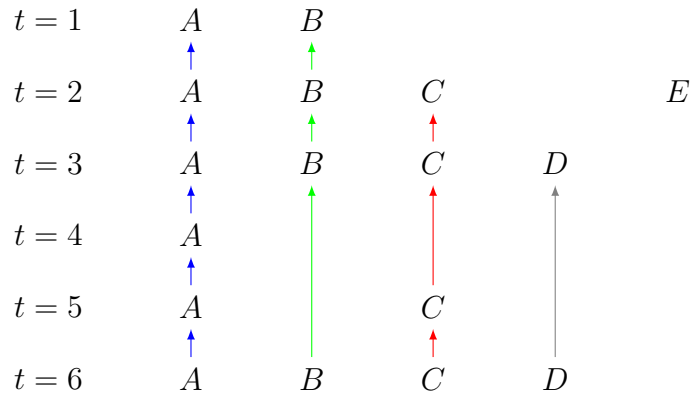
Suppose the pricing currency is the dollar and we want to identify price changes in dollars. First, we compare export prices denominated in dollars over time and at the firm-product-destination level as illustrated in the following figure. Price changes less than 5% are marked with “x”.



We then set the batch of individual prices associated with a price changes below $\pm 5\%$ ($p_{B,5}, p_{C,4}, p_{D,4}, p_{E,4}$) to missing. This gives

$$\begin{bmatrix} p_{A,1} & p_{B,1} & \cdot & \cdot & \cdot \\ p_{A,2} & p_{B,2} & p_{C,2} & \cdot & \cdot \\ p_{A,3} & p_{B,3} & p_{C,3} & p_{D,3} & p_{E,3} \\ p_{A,4} & \cdot & \cdot & \cdot & \cdot \\ p_{A,5} & \cdot & p_{C,5} & \cdot & \cdot \\ p_{A,6} & p_{B,6} & p_{C,6} & p_{D,6} & \cdot \end{bmatrix}$$

Note that we did not treat $p_{C,5}$ as missing at this stage. This is because $|p_{C,5} - p_{C,3}|$ could be $> 5\%$ even if both $|p_{C,4} - p_{C,3}| < 5\%$ and $|p_{C,5} - p_{C,4}| < 5\%$.⁶² Rather, we repeat the above step using the remaining observations as illustrated below.



In this example, we indeed find $|p_{C,5} - p_{C,3}| > 5\%$ and the remaining pattern is given as follows.

⁶²Variables are in logs.

As no prices are sticky, we can stop the iteration.⁶³ Note that as no price changes can be formulated for the single trade record $p_{E,2}$, this observation is dropped from our sample.

$$\begin{bmatrix} p_{A,1} & p_{B,1} & \cdot & \cdot & \cdot \\ p_{A,2} & p_{B,2} & p_{C,2} & \cdot & \cdot \\ p_{A,3} & p_{B,3} & p_{C,3} & p_{D,3} & \cdot \\ p_{A,4} & \cdot & \cdot & \cdot & \cdot \\ p_{A,5} & \cdot & p_{C,5} & \cdot & \cdot \\ p_{A,6} & p_{B,6} & p_{C,6} & p_{D,6} & \cdot \end{bmatrix}$$

Now we have identified the universe observations with price changes. The next step is to formulate the trade pattern dummy.

$t = 1$	A	B		
$t = 2$	A	B	C	
$t = 3$	A	B	C	D
$t = 4$	A			
$t = 5$	A		C	
$t = 6$	A	B	C	D

In this example, we find 5 trade patterns, i.e., $A - B$, $A - B - C$, $A - B - C - D$, A , $A - C$, but only one pattern, $A - B - C - D$, which appears at least two times. To compare the change in relative prices across destinations, we require the same trade pattern be observed at least two times in the price-change-filtered dataset.⁶⁴ In the example presented above, only prices within the trade pattern $A - B - C - D$ will be compared because it is the unique pattern to appear two times. In the real customs database with hundreds of thousands of firms, each trade pattern typically is associated with many firm-product-time triplets. The destination demeaned (relative) price is first constructed at the firm-product-time level (i.e., this is the first step of the TPSFE estimation procedure) and regressions are then run by adding trade pattern fixed effects⁶⁵ (i.e., this is the second step of the TPSFE estimator).

⁶³In the real dataset, the algorithm often needs to iterate several times before reaching this stage.

⁶⁴Essentially, by formulating trade pattern fixed effects, we are restricting the comparison within a comparable environment. Firms switch trade patterns for a reason. Restricting the analysis to the same trade pattern also controls for other unobserved demand factors affecting the relative prices.

⁶⁵To construct trade pattern fixed effect dummies, we prefix the destination country in front of the trade pattern, e.g. $A - A - B - C - D$, $B - A - B - C - D$, $C - A - B - C - D$, $D - A - B - C - D$. Prefixing the destination country code ensures the “destination-trade pattern” comparison of prices and exchange rates.

Year	Country	Value	Price
2001	Germany	7957	.43
	Indonesia	28543	.49
	Italy	2416699	.47
	Thailand	6900	.38
	Vietnam	9391	.49
2002	Indonesia	69241	.48
	Italy	1415535	.54
	Latvia	9302	.53
	Philippines	9126	.52
	South Korea	8908	.48
2003	Germany	47924	.49
	Japan	54450	.36
	Philippines	9126	.52

Table 20: A real data example of changing trade patterns: Exports of tomato paste (HS 20029010) by the firm with identifier 6512910023

C.5 Data cleaning process and the number of observations

Table 21: Stage 0 - Raw

	Observations	Destinations	8-digit HS Codes	Firms	Years
Number of unique values	108,465,375	246	10,002	581,141	15

Table 22: Stage 1 - Drop exports to the U.S. and Hong Kong

	Observations	Destinations	8-digit HS Codes	Firms	Years
Number of unique values	92,308,538	244	9,959	545,175	15

Table 23: Stage 2 - Drop if the destination identifier, product identifier or value of exports is missing; Drop duplicated company names

	Observations	Destinations	8-digit HS Codes	Firms	Years
Number of unique values	92,177,750	243	9,954	545,133	15

Table 24: Stage 3 - Collapse at firm-product-destination-year level; integrating 17 eurozone countries into a single economic entity

	Observations	Destinations	8-digit HS Codes	Firms	Years
Number of unique values	83,439,048	227	9,954	545,133	15

A product is defined as 8-digit HS code + a form of commerce dummy + a CCHS classification dummy. More precisely, this could be described as a variety but we used the term product throughout the paper.

Table 25: Stage 4 - Drop observations if bilateral exchange rates or destination CPI is missing

	Observations	Destinations	8-digit HS	6-digit HS	Firms	Years
Number of unique values	77,511,443	157	9,929	5,867	532,530	15

Table 26: Stage 5 - Filtering price changes (in logs, denominated in RMB) < 0.05 at the firm-product-destination level following the method described by C.4

	Observations	Destinations	Products	6-digit HS	Firms	Years
Number of unique values	72,792,147	157	20,347	5,867	532,530	15

Our method uses both destination and time variations to identify markup and quantity responses to prices and exchange rate shocks. We drop single-year or single-destination observations.

Table 27: Stage 6 - Drop single-destination firm-product-year triplets

	Observations	Destinations	Products	6-digit HS	Firms	Years
Number of unique values	50,355,418	157	17,258	5,446	356,541	15

Table 28: Stage 7 - Drop single-year firm-product-destination triplets

	Observations	Destinations	Products	6-digit HS	Firms	Years
Number of unique values	23,750,519	154	14,611	5,051	238,610	15

Finally, we drop “single-year firm-product-trade-pattern triplets.” Including these observations will not change the estimates obtained from the TPSFE estimator because they do not provide the within firm, product and destination *intertemporal variation* upon which the estimator relies.

Table 29: Stage 8 - Formulating trade pattern; Drop single-year firm-product-trade-pattern triplets

	Observations	Destinations	Products	6-digit HS	Firms	Years
Number of unique values	5,940,011	154	14,172	5,007	209,499	15

C.6 Macroeconomic Data

Macroeconomic variables on nominal bilateral exchange rates, CPI of all destination countries (normalized so that CPI=100 in 2010 for all series), real GDP (constant 2005 US dollars), the import to GDP ratio come from the World Bank. We construct the nominal bilateral exchange rate in renminbi per unit of destination currency from China’s official exchange rate (rmb per US\$) and each destination country’s official exchange rate in local currency units per US\$ (all series are the yearly average rate). These variables are available for 154 destination countries in our sample.

In our empirical analysis, we focus on nominal rather than real bilateral exchange rates. Estimations using real exchange rates implicitly impose a one-to-one linear relationship between each nominal bilateral exchange rate and the ratio of CPI indices (i.e., destination CPI/origin CPI). Real exchange rate series which embed this restriction are highly correlated with nominal exchange rates. Since nominal exchange rate series are significantly more volatile over time than the ratio of CPI indices, movements in the real exchange rate are primarily driven by fluctuations in nominal exchange rates. It is not clear if restricting these two variables with significantly different volatilities into a one-to-one linear relationship is justified in exchange rate pass through studies. Throughout our analysis, we enter nominal bilateral exchange rates and destination CPI index as two separate variables.

As we discussed in previous sections, taking time differences in an endogenously unbalanced panel tends to make the unobserved marginal cost uncontrollable and introduce potential biases. In all our regressions, we enter variables in logged levels. A concern of using logged levels rather than time differences is that nominal series, such as exchange rates and CPI indices, cannot be compared directly across countries. In solving this compatibility problem, it is useful to think of the nominal series as a compatible measure plus an unobserved destination specific drift, i.e.,

$$e_{dt}^{nominal} = e_{dt}^{compatible} + \mu_d.$$

Thanks to our trade pattern fixed effects, our proposed approach is robust to this type of destination specific drift, which enables us to correctly disentangle the effect of nominal exchange rate fluctuations from destination CPI movements.

C.7 Additional Information on the CCHS Classification

To illustrate how measure words encode meaning in Chinese, consider the problem of counting three small objects. Chinese grammar requires the use of a measure word between the number and the noun being counted. Thus, to say “three ballpoint pens,” or “three kitchen knives,” one would say the English equivalent of “three long-thin-cylindrical-objects [zhī, 支] ballpoint pens” and “three objects-with-a-handle [bǎ, 把] kitchen knives.”⁶⁶ Both of these objects, ballpoint pens and kitchen knives, are measured with count classifiers (zhī and bǎ, respectively) and are, in our classification, high differentiation goods. In contrast, products reported with mass classifiers including kilograms (cereal grains, industrial chemicals), meters (cotton fabric, photographic film), and cubic meters (chemical gases, lumber) are low differentiation goods. Because measure words

⁶⁶English uses measure words; “two dozen eggs” and “a herd of cattle” are two examples. The difference lies in the extent to which unique measure words exist for Chinese nouns and the fact that proper Chinese grammar always requires the use of the appropriate measure word when counting.

encode physical features of the object being counted, they allow us to identify when statistical reporting is for a high versus low differentiation good. According to Cheng and Sybesma (1999), “...the distinction between the two types of classifiers is made with explicit reference to two different types of nouns: nouns that come with a built-in semantic partitioning and nouns that do not – that is, count nouns and mass nouns.” While it is possible that our proposed system could lead to some amount of mis-classification because there are some count nouns which exhibit low levels of differentiation and some mass nouns which are quite differentiated, a Chinese-linguistics-based approach to goods classification is still valuable for two reasons. First, nouns with built-in semantic partitioning such as televisions, microscopes and automobiles are high differentiation goods regardless of whether their trade is reported in metric tonnes or units. This is a key advantage of relying on Chinese measure words to classify tradeable goods: measure words clearly identify objects that inherently are semantically partitioned (i.e. are distinct objects), relative to goods that exist as undifferentiated masses. Second, the choice of the measure word is predetermined in the minds of Chinese speakers by grammatical rules that have existed for centuries. This choice is clearly exogenous to and predates modern statistical reporting systems.⁶⁷

To illustrate the variety of count classifiers used for similar objects, note that “Women’s or girls’ suits of synthetic fibres, knitted or crocheted” (HS61042300) and “Women’s or girls’ jackets & blazers, of synthetic fibres, knitted or crocheted” (HS61043300) are measured with two distinct Chinese count classifiers, “套” and “件,” respectively. Further, table 30 documents the intrinsic information content of the measurement units for HS04 product groups 8211 and 8212. The Chinese language descriptions of all of these HS08 products conveys the similarity across products; each Chinese description contains the Chinese character ‘dao’ (刀), which means ‘knife’ and is a part of longer compound words including table knife and razor. Interestingly, three different Chinese count classifiers, “tào, 套,” “bǎ, 把,” and “piàn, 片,” are used to count sets of knives (HS82111000), knives and razors (HS82119100 - HS82121000), and razor blades (HS82122000), respectively.

⁶⁷A subtle distinction arises between the statistical reporting of trade data in Japan and China. The Japanese language also requires the use of measure words, aka ‘counters,’ when counting. However, documentation for Japanese trade declarations instructs that the measurement unit “NO” (the English abbreviation for number) should be used for reporting quantity and explains that this Western measure word subsumes 11 Japanese language measure words (個、本、枚、頭、羽、匹、台、両、機、隻、着). These instructions on Japanese Customs declarations validate our approach for China because these 11 Japanese measure words are linguistically similar to Chinese count classifiers. However, because the reporting is based on a Western word, the choice of a measurement unit in Japanese data might not be exogenously driven by the structure of the Japanese language. Thus, there is a reason for basing the classification of goods using linguistic information on Chinese rather than Japanese customs data. We thank Taiji Furusawa, Keiko Ito, and Tomohiko Inui for answering our questions about the use of measure words in Japanese trade data.

Table 30: Examples of count classifiers in the Chinese Customs Database

Quantity Measure	HS08 Code	English Description	Chinese Description
tào, 套	82111000	Sets of assorted knives	成套的刀
bǎ, 把	82119100	Table knives having fixed blades	刃面固定的餐刀
bǎ, 把	82119200	Other knives having fixed blades	其他刃面固定的刀
bǎ, 把	82119300	Pocket & pen knives & other knives with folding blades	可换刃面的刀
bǎ, 把	82121000	Razors	剃刀
piàn, 片	82122000	Safety razor blades, incl razor blade blanks in strips	安全刀片, 包括未分开的刀片条

The most frequently used mass classifier is kilograms. Examples of other mass classifiers include meters for “Knitted or crocheted fabric of cotton, width $\leq 30\text{cm}$ ” (HS60032000), square meters for “Carpets & floor coverings of man-made textile fibres” (HS57019010), and liters for “Beer made from malt” (HS22030000).

In table 31, we provide a breakdown of our CCHS classification within the UN’s Broad Economic Categories (BEC) of intermediate, consumption and other goods. The majority of intermediate goods are low differentiation and the majority of consumption goods are high differentiation, but all BEC groups include both high differentiation and low differentiation goods.

Table 31: Classification of differentiated goods: CCHS vs. BEC

(a) Share of goods by classification: observation weighted

	Corsetti-Crowley-Han-Song (CCHS)		
	Low Differentiation / (Mass nouns)	High Differentiation / (Count nouns)	
BEC			
Intermediate	29.8	2.7	32.5
Consumption	14.3	20.1	34.4
Other [†]	15.0	18.1	33.1
	59.1	40.9	100.0

(b) Share of goods by classification: value weighted

	Corsetti-Crowley-Han-Song (CCHS)		
	Low Differentiation / (Mass nouns)	High Differentiation / (Count nouns)	
BEC			
Intermediate	26.0	3.9	29.9
Consumption	8.6	14.0	22.6
Other [†]	12.6	34.9	47.5
	47.2	52.8	100.0

Notes: Share measures are calculated based on Chinese exports to all countries including Hong Kong and the United States during periods 2000-2014. [†]: The “Other” category refers to capital goods and unclassified products by BEC classification, such as nuclear weapons.

For twenty industrial sectors, Table 32 reports the share of products in each sector that are classified as high differentiation according to the Corsetti, Crowley, Han, and Song (CCHS) classification. For the 36 measure words in our estimation dataset, we categorize goods measured with the 24 count classifiers as high differentiation, while goods measured with 12 mass classifiers are treated as low differentiation.⁶⁸ Column one lists the HS chapters that define the sector. The second column provides the sector’s share in China’s total exports over 2000-2014. Quantitatively, important export sectors with large shares of high differentiation goods include optical and photographic equipment (79.7 percent), machinery and mechanical appliances (73.1 percent), textiles and apparel (68.4 percent), vehicles and aircraft (66.1 percent), stone and plaster articles (65.0 percent), leather goods (58.6 percent), and plastics and rubber articles (15.0 percent). The share of

⁶⁸We thank Prof. Lisa Lai-Shen Cheng for her feedback on our classification of measure words from the Chinese Customs Database into count and mass classifiers.

Table 32: CCHS product classification across sectors

Sector (HS chapters)	Sector's share of total exports	Value share of CCHS high differentiation products within sector
1-5 Live animals; animal products	0.8	4.0
6-14 Vegetable products	1.0	0.6
15 Animal/vegetable fats	0.0	0.0
16-24 Prepared foodstuffs	1.4	0.0
25-27 Mineral products	2.1	0.0
28-38 Products of chemical and allied industries	4.6	0.2
39-40 Plastics/rubber articles	3.4	15.0
41-43 Rawhides/leather articles, furs	1.6	58.6
44-46 Wood and articles of wood	0.8	0.5
47-49 Pulp of wood/other fibrous cellulosic material	0.8	0.0
50-63 Textile and textile articles	13.2	68.4
64-67 Footwear, headgear, etc.	2.9	43.5
68-70 Misc. manufactured articles	1.8	3.2
71 Precious or semiprec. stones	1.4	0.0
72-83 Base metals and articles of base metals	7.7	1.9
84-85 Machinery and mechanical appliances, etc.	42.2	73.1
86-89 Vehicles, aircraft, etc.	4.7	66.1
90-92 Optical, photographic equipment etc.	3.5	79.7
93 Arms and ammunition	0.0	82.5
94-96 Articles of stone, plaster, etc.	6.0	65.0
97 Works of art, antiques	0.1	60.8

Source: Compiled by the authors from exports of Chinese Customs Database, 2000-2014, using the Corsetti, Crowley, Han and Song (CCHS) classification.

high differentiation products across sectors varies widely, but lines up with our priors. Machinery and mechanical appliances and vehicles and aircraft are dominated by CCHS high differentiation goods while virtually all chemicals and base metal products are low differentiation.

C.7.1 Rauch classification for China exports

In order to provide a Rauch classification for each product in the Chinese Customs Database, it was necessary to concord the SITC Rev. 2 product codes from Rauch’s classification to HS06 product codes used in the Chinese Customs Database.

Table 33: 6-digit HS code matching rate with Rauch classification using HS2002toSITC2 concordance table and the conservative version of Rauch classification

	Number of 6-digit HS codes	Percent
Matched (Unique Rauch Classification for Each HS Code)	4,589	78.30
Unmatched (Multiple Rauch Classifications for Each HS Code)	1,272	21.70
Total	5,861	100.00

Table 34: 6-digit HS code matching rate with Rauch classification using HS2007toSITC2 concordance table and the liberal version of Rauch classification

	Number of 6-digit HS codes	Percent
Matched (Unique Rauch Classification for Each HS Code)	4,438	80.93
Unmatched (Multiple Rauch Classifications for Each HS Code)	1,046	19.07
Total	5,484	100.00